

# PREDICTING THE MATERNAL RISK DURING CHILDBIRTH

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CMP-SCI 5300  
Semester project

## 1 Introduction

**The maternal risk** is determined by several factors during the childbirth, this project is aim to classify risk levels and predict whether the maternal is in danger. Even though there are many aspects related to the process of childbirth, the goal here is to build a neural network that distinguish high/low risk of maternal death regarding to the given data categories.

In the selected data set "Maternal health risk" [1], there are total of 1014 instances with no missing values. The attribute age, systolic/diastolic blood pressure, blood sugar, body temperature, and heart rate are considered given inputs, which are all close related to the status of maternal during the birth and by defining what factors lead to a high risk, corresponding prevention may applied in order to keep maternal away from death.

Personally, making model according to problem that related to health care is more meaningful compare to any other classification. Even though this is a quiet brief model of neural network, which might not ever get chance to become a real-world application, the given input seem very reasonable and relevant in order to determine the output of risk level, which gives more credibility in the prediction process.

## 2 Data Set

### 2.1 Data cleaning

**Reform the multi-classified data into binary**, as known as data cleaning for selected data set is straight forward, age, systolic/diastolic blood pressure, blood sugar, body temperature, and heart rate are all integer values and they are not required to be binary since these are going to be our inputs, the output value, risk-level, is 3-variable classification defined by high/mid/low risks. where  $high(272) < mid(336) < low(406)$ . Considering the balance of the data set, we merge mid-risk class into

$$x_h = \frac{x_{high}}{sum(x)}, x_l = \frac{x_{low}}{sum(x)} \quad (1)$$

We have results:

level	Number	Percentage
High(1)	608	59.96%
Low(0)	406	40.04%
Total	1014	100%

Table 1: Two classes are distributed in balance

### 2.2 Data Normalization

**To achieve feature scaling**, because we have no extreme value among the inputs, standardization is not necessary, the function applied is the mean-range normalization function[2]:

$$x' = \frac{X - \mu}{X_{max} - X_{min}} \quad (2)$$

Usually, feature scaling is used when each category of data do not have the same range scales, which in our case, the value range of systolic blood pressure obviously differs from blood sugar; these difference can slow down the learning of a model. When we apply Gradient Descent in both normalized and non-normalized data set, Gradient Descent converges to the minimum faster if the input is normalized.

**Now, let's give a taste** of mean-range normalization, the charts shown below indicate the first 3 rows of data before and after normalization:

Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate
25	130	80	15	98	86
35	140	90	13	98	70
29	90	70	8	100	80

Table 2: First 3 rows before normalization

Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate
-0.08	0.19	0.07	0.48	-0.13	0.14
0.09	0.30	0.27	0.33	-0.13	-0.05
-0.01	-0.26	-0.13	-0.06	0.27	0.07

Table 3: First 3 rows after normalization

**As the tables show**, the range of each attribute is narrowed down to same interval  $[-1, 1]$ . The attribute In-risk(RiskLevel before cleaning), is exclusive.

## 2.3 Data Overview

Before constructing the model, It is better to go through the data set in detail.

### 2.3.1 Histogram

**We can see the distribution via histogram**, the graph shown below will illustrate distribution of each attribute, BloodSugar, BodyTemp, and HeartRate are reasonably centralized:

Figure 1)

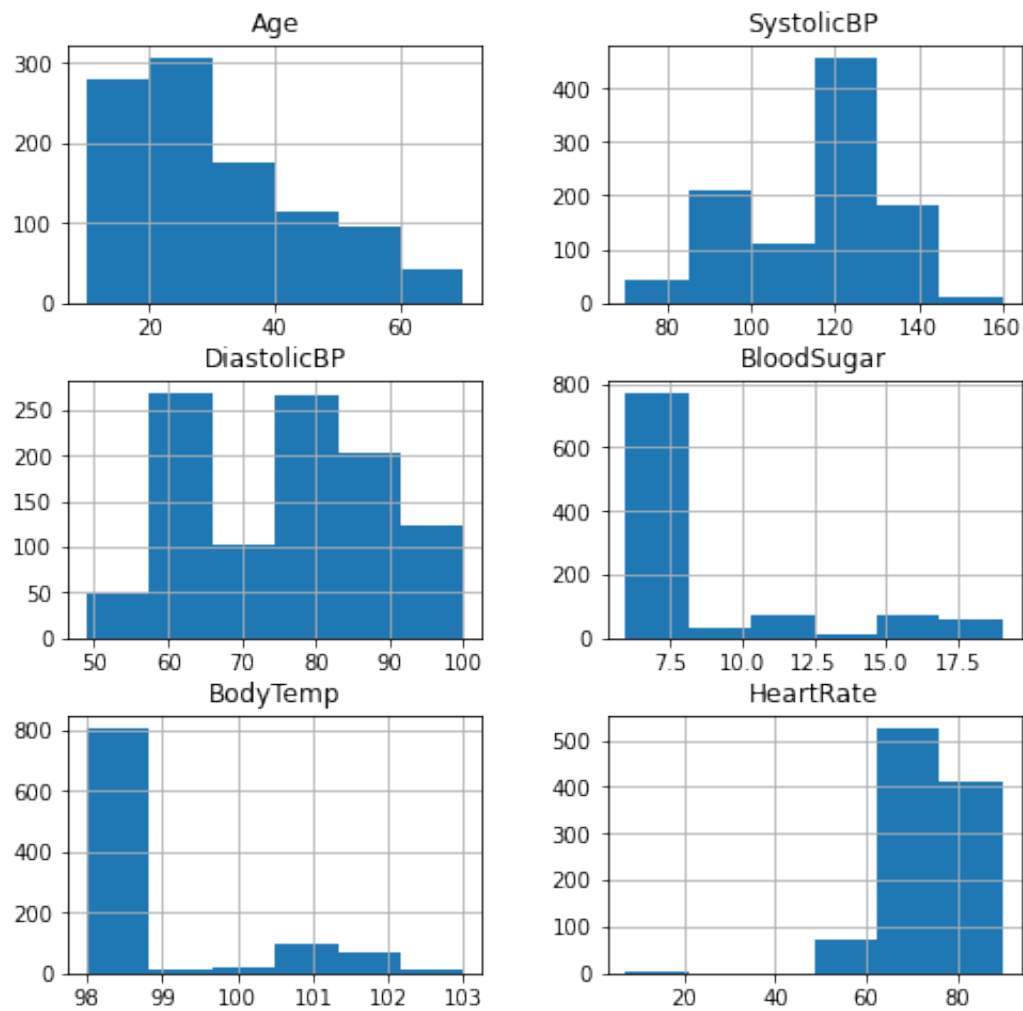


Figure 1: the distribution histogram of each input attribute

Figure 2)

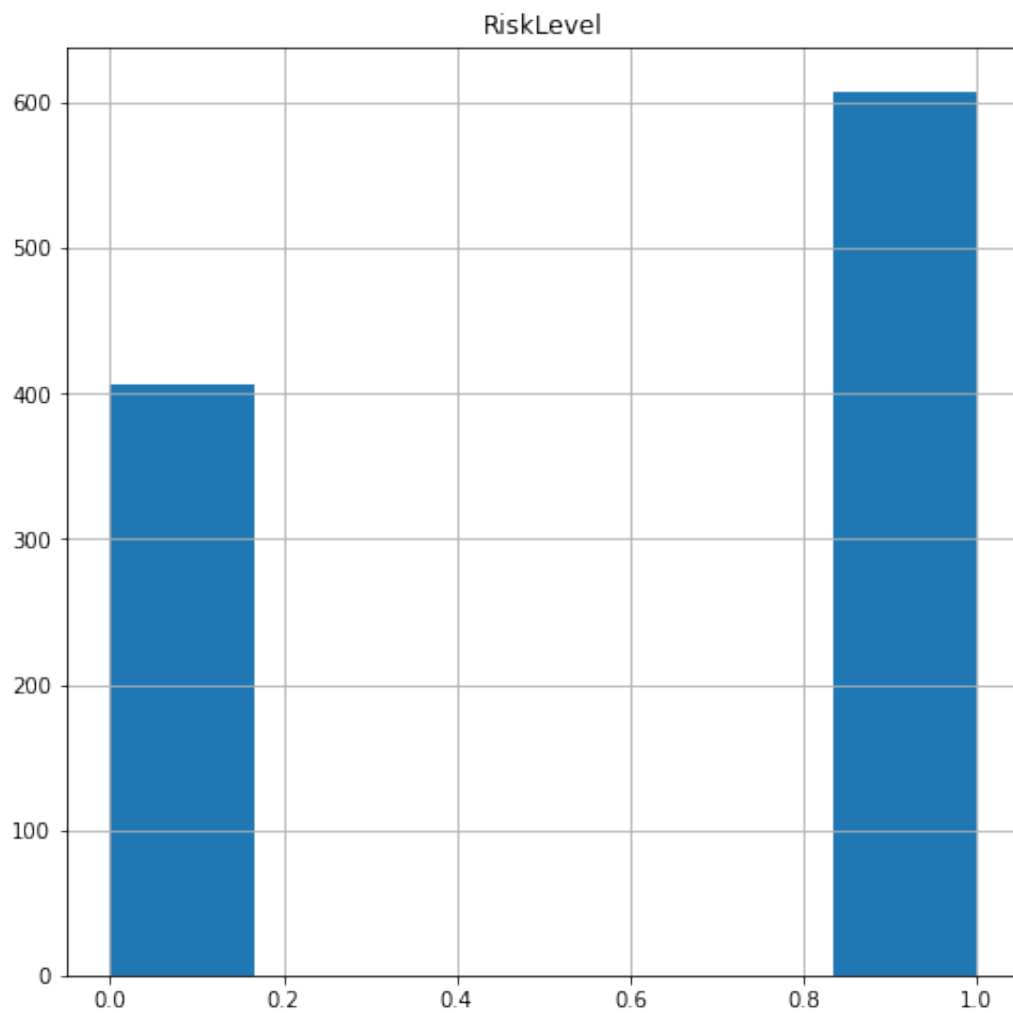


Figure 2: the distribution histogram for output attribute

### 2.3.2 data significance

**Age:** The maternal sample's age, extreme age is more likely to develop pregnancy-related high blood pressure and anemia (lack of healthy red blood cells).

**Systolic Blood pressure:** indicates how much pressure your blood is exerting against your artery walls when the heart beats. Monitoring blood pressure is important before, during, and after pregnancy.

**Diastolic blood pressure:** The pressure of maternal sample's blood exerting against artery walls while the heart is resting between beats. Monitoring blood pressure is important before, during, and after pregnancy.

**Blood sugar:** blood sugar concentration, High blood glucose can increase the chance that maternal samples will have a miscarriage or damage of the health

**Body temperature:** changes of body temperature can influence metabolic changes in different nutrients of pregnant women.

**Heart rate:** During childbirth, maternal sample's heart pumps more blood each minute and heart rate increases, especially when push, they will have abrupt changes in blood flow and pressure.

**Besides,** all other related information are contained in the table shown below:

	max	min	mean	median	std
age	70.00	10.00	29.87	26.00	13.47
systolicBP	160.00	70.00	113.20	120.00	18.39
diastolicBP	100.00	49.00	76.46	80.00	13.88
BloodSugar	19.00	6.00	8.73	7.50	3.29
BodyTemp	103.00	98.00	98.67	98.00	1.37
HeartRate	90.00	7.00	74.30	76.00	8.08

Table 4: Input data overview information

## 3 Modeling

**In this section**, I will show how our data set fits into different modeling mechanisms and how each one of the techniques affects our accuracy. In order to do this, we apply python library called Tensorflow.

1. `from tensorflow.keras.models import Sequential`
2. `from tensorflow.keras.layers import Dense`

### 3.1 logistic regression

**First of all** let's see how does the data set fit the logistic regression model. After assigning variable `model = Sequential()`, we now have a deep learning modeling environment where we can add layers into the network, every unit in a layer is connected to every unit in the previous layer. However, for now we will have only one layer with one node to do the logistic regression[3].

**In order to compile the model**, we use following function parameters:

`<loss = 'binary_crossentropy'>`

Since this is binary classification model (0 or 1), we use it to determine our loss.

`<optimizer = 'rmsprop'>`

'rmsprop' is a gradient based optimization technique, it uses an adaptive learning rate which changes over time.

`<metrics = 'accuracy'>`

Which represents the overall Accuracy that is essentially tells us out of all of the reference sites what proportion were mapped correctly.

**After** setting epoch to 256 and repeat several times, here is result of last 5 training of our model in last reputation of epochs of 256:

epochs	loss	accuracy
252/256	0.5580	0.6726
253/256	0.5516	0.6746
254/256	0.5556	0.6785
255/256	0.5646	0.6686
256/256	0.5564	0.6716

Table 5: single layer training result

Below is the first 10 predictions the model makes compare to original output 'Y' value (bad predictions are highlighted):

TrueValue	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00
Prediction	0.99	0.95	0.26	0.52	0.40	0.59	0.61	0.63	0.26	1.00

Table 6: single layer accuracy comparison

**Since** we are using only one layer here, I think this is a acceptable result, however, to achieve higher accuracy, we might build a model with multiple layers and nodes.

### 3.2 multi-layered model

A **multi-layered** model is more precise than what we have seen in 3.1 since it involves more weights/rates and biases that tweak the prediction over and over.

In this model, I have added up to 4 layers in total, where first layer has 16 node, and second layer has 8 nodes, 4 for third layer, and also, last node in fourth layer. The thing we should pay attention here is that, first three layer we will use **activation = 'relu'** since they are not binary classification, and last layer we use **activation = 'sigmoid'**. Below is the description chart of layers:



**Figure 3)**

Model: "sequential\_5"

Layer (type)	Output Shape	Param #
dense_18 (Dense)	(None, 16)	112
dense_19 (Dense)	(None, 8)	136
dense_20 (Dense)	(None, 4)	36
dense_21 (Dense)	(None, 1)	5

=====  
Total params: 289  
Trainable params: 289  
Non-trainable params: 0

Figure 3: Neural networks in layers

**As** we can see, there are 289 params since we have 6 categories of input plus bias, which is  $(6 + 1) * 16 + (16 + 1) * 8 + (8 + 1) * 4 + (4 + 1) * 1 = 289$ , another good way to see this is via visualization (see **Figure 4**).

Just like 3.1, below is the table showing last 5 execution of running epochs, this time I set epochs = 2560 and 4 repeated 4 times.

epochs	loss	accuracy
2556/2560	0.1928	0.9043
2557/2560	0.2018	0.9093
2558/2560	0.2034	0.9083
2559/2560	0.2025	0.9043
2560/2560	0.1963	0.9132

Table 7: multi-layered training result

Figure 4)

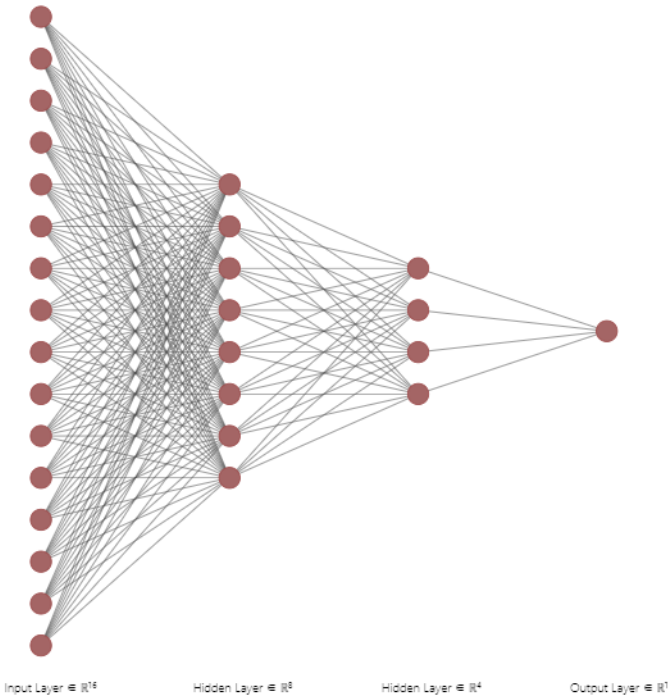


Figure 4: multi-layered Neural networks model

To see how well it can predict after all, here are first 10 values of comparison between true values and predictions where bad predictions are highlighted:

TrueValue	1.00	1.00	1.00	1.00	0.00	1.00	1.00	1.00	1.00	1.00
Prediction	1.00	1.00	1.00	1.00	0.48	1.00	1.00	1.00	0.43	1.00

Table 8: multi-layered accuracy comparison

**It is obvious** that multi-layered model performs better than our single-layered model, there are 8 perfect guess in first 10 values.

### 3.3 Splitting Dataset

**In this section**, the entire data set is divided into 2 sub-dataset after shuffling by `np.random.shuffle` function, which are training set and validation set, where training set take 80% of all data and validation set will take 20% of the entire data and validation set will be used to test and monitor whether two sets are on the balance of generalization.

**Before Building the model**, both sets are sharing the same normalization factors as introduced below:

$$X_{train} = \frac{X_{train} - \mu_{train}}{X_{train_{max}} - X_{train_{min}}} \quad (3)$$

$$X_{Valid} = X_{Valid} - \mu_{train} \quad (4)$$

$$X_{Valid} = \frac{X_{valid}}{X_{train_{max}} - X_{train_{min}}} \quad (5)$$

**These operations** ensure that validation set are using training set's mean and range.

### 3.4 Evaluating different models

**Since different hype-parameters and different model** do affect the performing of accuracy, we want to try as much as we can to find the highest accuracy when input is validation set.

**Recall from phrase 1**, the number of high risk cases are 608, which takes 59.96% of total cases, this is considered our base-line accuracy. Even though any accuracy above this percentage is acceptable, we do want to find out that the highest validation set accuracy is under what kind of environment.

**The tables shown below** illustrate the differences between predicting training set and validation set under different conditions. For binary output, we always want the output layer to be "sigmoid", also, holding loss to "binary\_crossentropy" and metrix to "accuracy" as default. The changes in this case are: using optimizer as **rmsprop** and **"relu"** for other layers for NNs that has many layers applicable :

dataset	model	layer	epochs	loss	accuracy	F1 score	precision
TRAIN	logistic regression	1	1536	0.50	0.72	0.77	0.76
VALID		1	1536	0.48	0.68	0.74	0.73
TRAIN	logistic regression	1	512	0.49	0.71	0.76	0.76
VALID		1	512	0.56	0.66	0.73	0.69
TRAIN	NNs 16-8-4-2-1	5	128	0.39	0.81	0.83	0.88
VALID		5	128	0.50	0.76	0.79	0.81
TRAIN	NNs 16-8-4-2-1	5	100	0.46	0.79	0.81	0.89
VALID		5	100	0.55	0.74	0.77	0.80
TRAIN	NNs 8-4-2-1	4	512	0.39	0.81	0.84	0.85
VALID		4	512	0.51	0.75	0.79	0.78
TRAIN	NNs 8-4-2-1	4	128	0.43	0.78	0.80	0.89
VALID		4	128	0.51	0.74	0.77	0.81
TRAIN	NNs 4-1	2	256	0.45	0.77	0.79	0.86
VALID		2	256	0.52	0.71	0.75	0.76

Table 9: train/valid comparison (rmsprop, sigmoid, relu +sigmoid for NNs)

The learning curves for the table 9 are shown below: [4]

Figure 5)

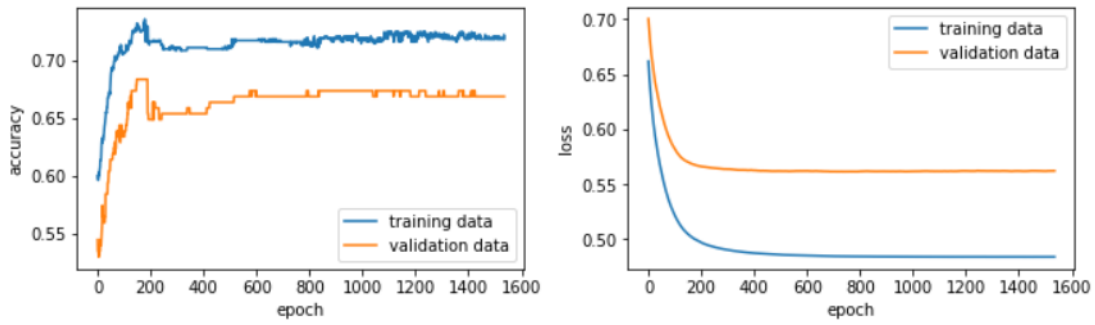


Figure 5: 1536 epochs comparison with logistic regression model

**1536 epochs comparison** seems to start over-fitting since the validation set on loss is slightly going upwards, for adjustment, let us see this with fewer epoch in Figure 6.

Figure 6)

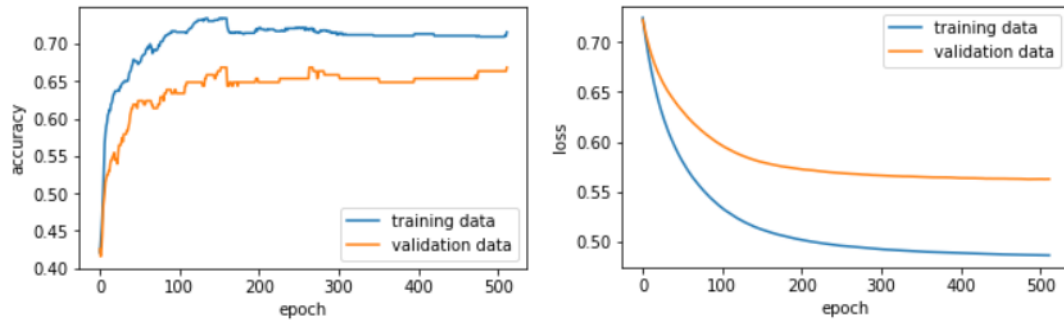


Figure 6: 512 epochs comparison with logistic regression model

**Figure 7)**

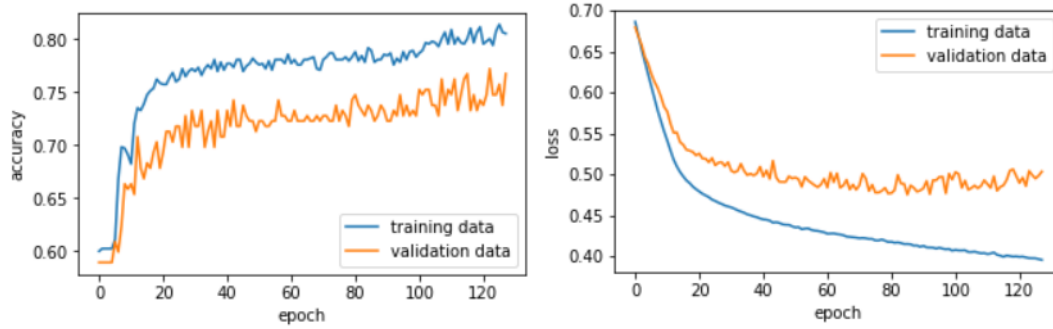


Figure 7: 128 epochs comparison with NNs 16-8-4-2-1 model

**Since** the NNs 16-8-4-2-1 model tends to be over-fitting somewhere about 100 epoch, We choose to run it with 128 epochs, this is not quiet generalized. When setting epochs to aound 100, it starts to under-fitting, so, this would be considered as best result.

**Figure 8)**

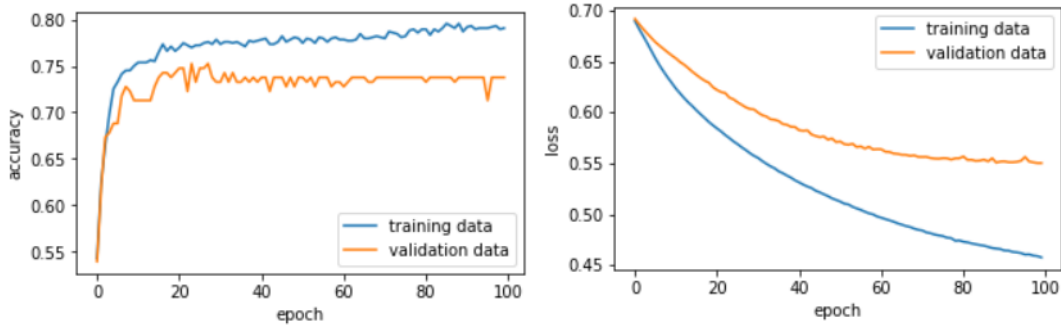


Figure 8: 100 epochs comparison with NNs 16-8-4-2-1 model

Even though training loss seems to be a little bit under-fitting (keep decreasing), but validation is going flat and giving higher validation set accuracy than epoch 128 does.

**Figure 9)**

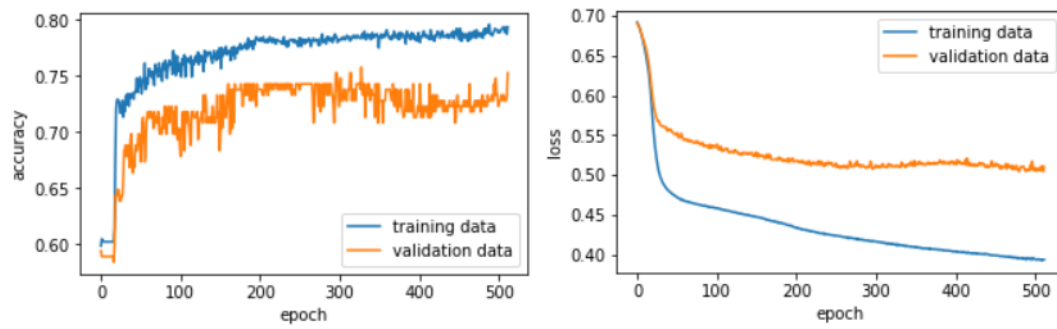


Figure 9: 512 epochs comparison with NNs 8-4-2-1 model

**Figure 9 is obviously over-fitting**, in order to make a better fit, we shall reduce the epoch taken, for example, 128 epoch as figure 10 shown below.

**Figure 10)**

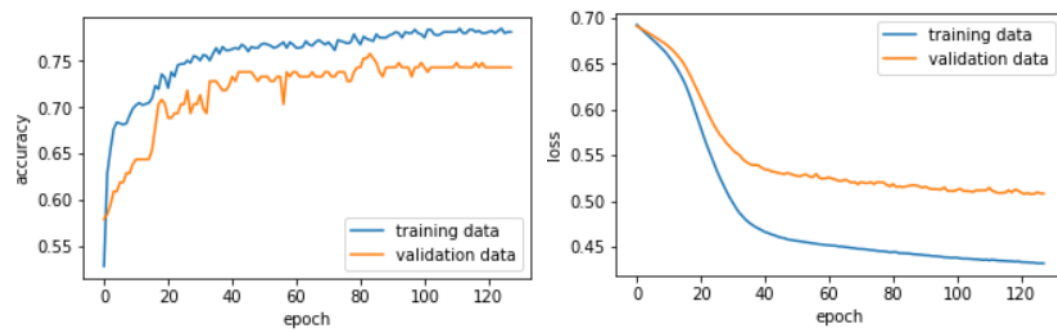


Figure 10: 128 epochs comparison with NNs 8-4-2-1 model

**Figure 11)**

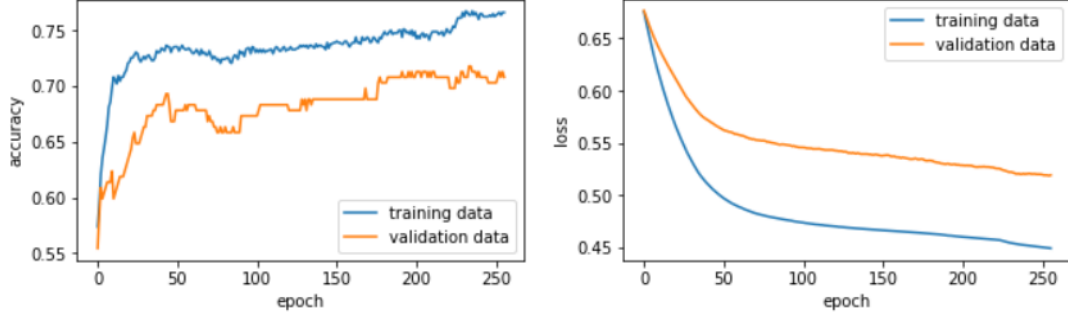


Figure 11: 256 epochs comparison with NNs 4-1 model

Since the dataset is relatively small, Figure 11 shows a big gap between training and validation set, and model 4-1 is not yielding the highest validation accuracy, so we stop from here.

Now, let activation change to **"adam"**. By the experience of Table 9, we see that model (NNs 16-8-4-2-1 128 epoch), (NNs 16-8-4-2-1 100 epoch) (NNs 8-4-2-1 512 epoch), and (NNs 8-4-2-1 128 epoch) are giving higher accuracy let's see if we can make any improvement on those models in the table 10 shown below

dataset	model	layer	epochs	loss	accuracy	F1 score	precision
TRAIN	NNs 16-8-4-2-1	5	128	0.40	0.81	0.83	0.90
VALID		5	128	0.50	0.74	0.77	0.81
TRAIN	NNs 16-8-4-2-1	5	256	0.37	0.81	0.83	0.90
VALID		5	256	0.51	0.71	0.74	0.79
TRAIN	NNs 8-4-2-1	4	512	0.37	0.83	0.85	0.90
VALID		4	512	0.48	0.77	0.82	0.82
TRAIN	NNs 8-4-2-1	4	128	0.43	0.79	0.81	0.89
VALID		4	128	0.51	0.73	0.76	0.79

Table 10: train/valid comparison (adam, sigmoid, relu +sigmoid for NNs)



The learning curves for the table 10 are shown below:  
Figure 12)

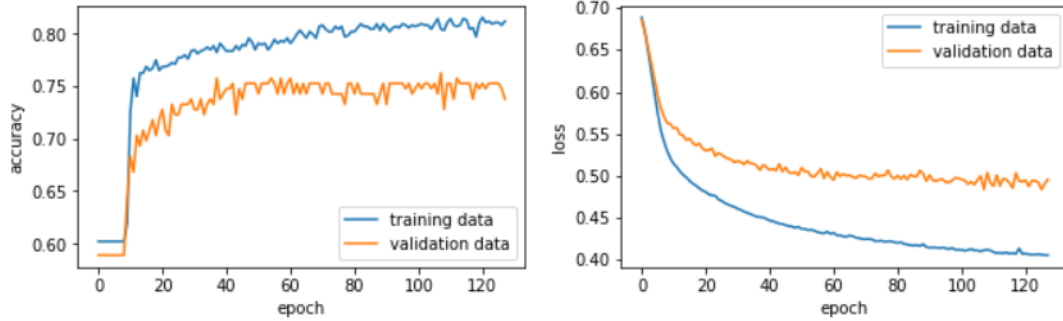


Figure 12: 128 epochs comparison with NNs 16-8-4-2-1 model

After testing 100 epoch, it seems to be under-fitting and result is poorer than using optimizer "rmsprop" in Table 9, let us try 256 epoch instead.

Figure 13)

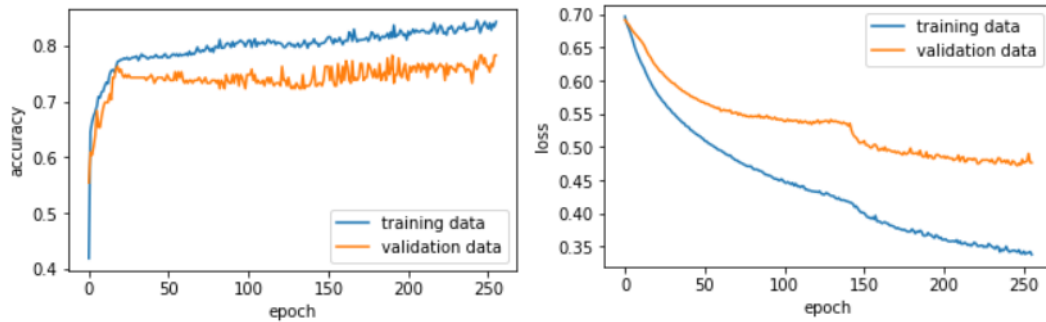


Figure 13: 256 epochs comparison with NNs 16-8-4-2-1 model

This time 256 epoch of model NNs 16-8-4-2-1 it's smoother and giving higher validation accuracy.

Figure 14)

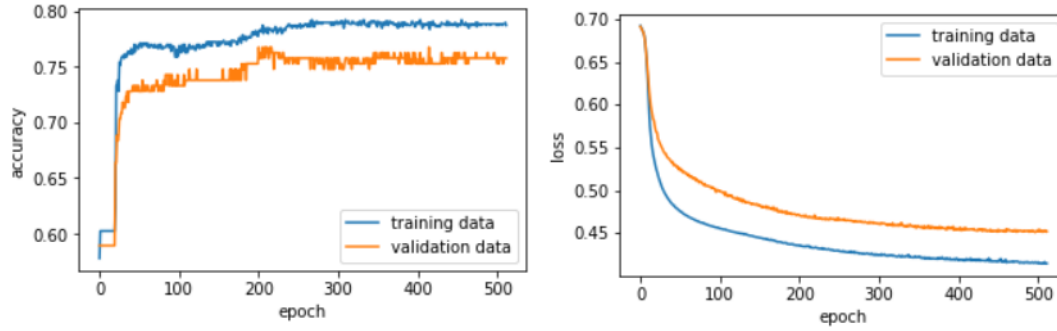


Figure 14: 512 epochs comparison with NNs 8-4-2-1 model

This model gives the smallest gap in loss learning curve, but accuracy is lower.

**Figure 15)**

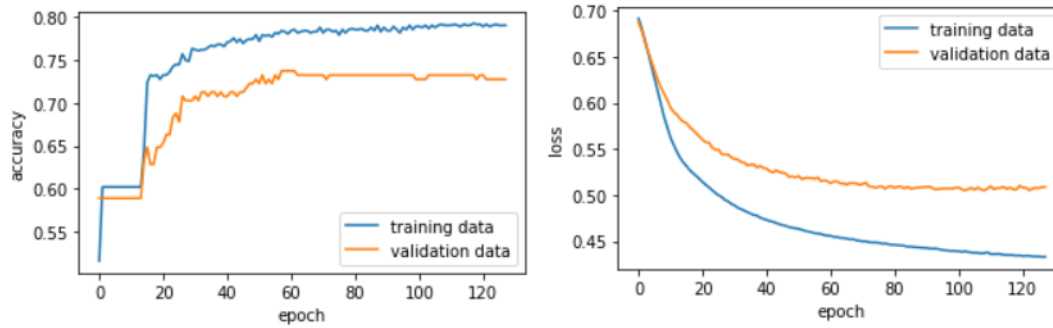


Figure 15: 128 epochs comparison with NNs 8-4-2-1 model

Figure 15 has too low validation accuracy, so it should not be considered. Now, let's compare (NNs 16-8-4-2-1 256 epoch) and (NNs 8-4-2-1 512 epoch).

First, let model (NNs 16-8-4-2-1 256 epoch) with activation change to "linear" except output layer remains "sigmoid", and remain other hype-parameter the as before (optimizer as "adam"), and model (NNs 8-4-2-1 512 epoch) with optimizer change to "sgd", and remain other hype-parameter the as before.

dataset	model	layer	epochs	loss	accuracy	F1 score	precision
TRAIN	NNs 16-8-4-2-1	5	256	0.48	0.72	0.77	0.76
VALID	(activation "linear")	5	256	0.56	0.67	0.74	0.69
TRAIN	NNs 8-4-2-1	4	512	0.46	0.78	0.79	0.90
VALID	(optimizer "sgd")	4	512	0.54	0.72	0.74	0.83

Table 11: train/valid comparison (different hype-parameter)

The learning curves for the table 11 are shown below:  
Figure 16)

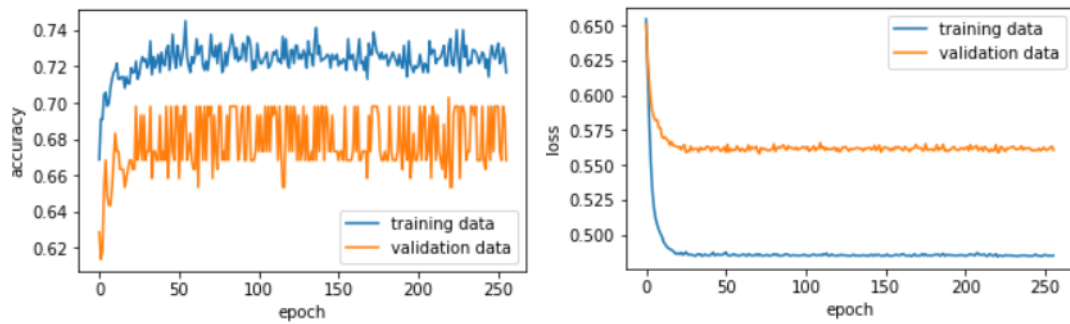


Figure 16: 256 epochs comparison with NNs 16-8-4-2-1 model

Figure 17)

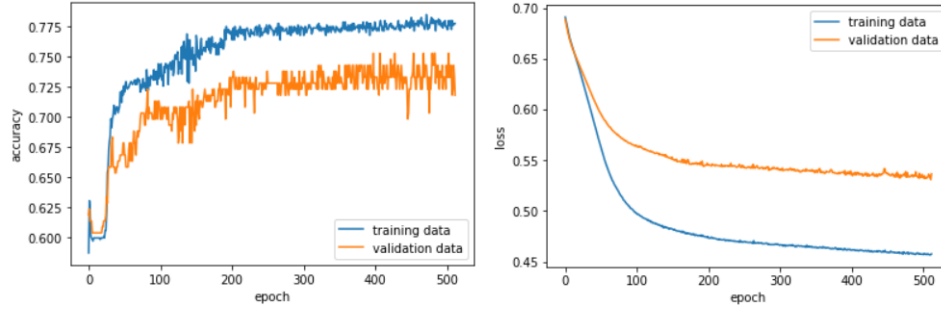


Figure 17: 512 epochs comparison with NNs 8-4-2-1 model

**After comparing Table 11 with Table 10, We Found neither "sgd" optimizer nor "linear" activation make the validation accuracy higher.**

**Overall,** The highest validation set accuracy is given by model (NNs 8-4-2-1 512 epoch) with hype-parameter activation "relu" with output layer "sigmoid", optimizer "adam", and metrix "accuracy". The result is

Validation set accuracy 0.77,  
 Loss 0.48,  
 F1 socre 0.82,  
 Precision 0.82

**Applying "EarlyStopping" and "ModelCheckpoint"** with patience of 10 and batch size of 2, model fitting stops at epoch 22, which means the epoch 12 is latest improvement made, the validation set accuracy at epoch 12 is 0.797 and its latest loss is 0.481 as Figure 18 shown below:

**Figure 18)**

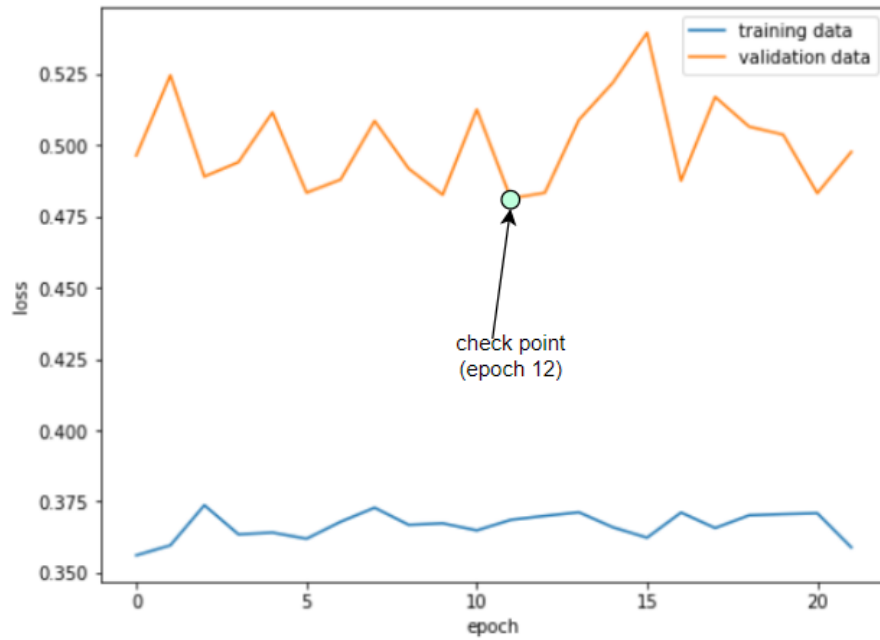


Figure 18: early stop of 22 epoch with checkpoint

**When we let output be an additional input**, which is let XTRAIN be 80% of entire dataset's rows and YTRAIN remains unchanged, same thing for XVALID, it will not have the output column of the 20% of the rows. Like it used in section 3.4, First starting with 1 neuron (single neuron is considered the lowest accuracy throughout the tests) and check for the accuracy.

**with 1 neuron model** compiled using "loss = binary\_crossentropy", "optimizer = adam", and "activation = sigmoid", result shown below:

**Figure 19)**

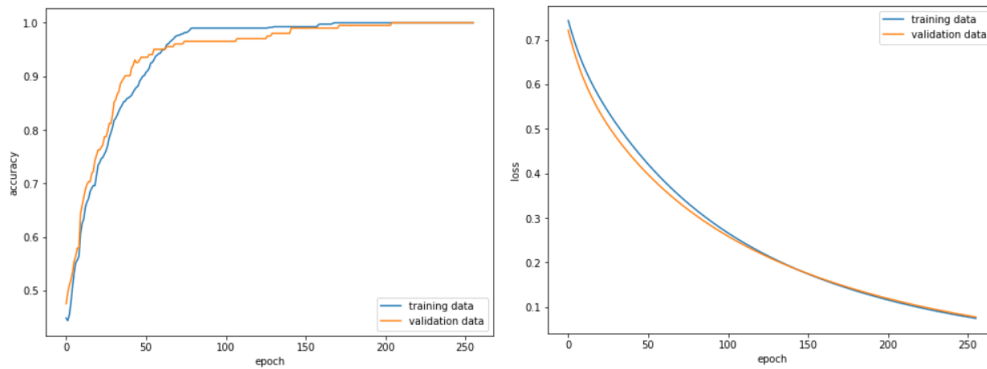


Figure 19: single neuron model with output as additional input

**After 256 epoch**, both Validation set and training set reach the 1.0 accuracy and their loss are less than 0.1, by conclusion, we only need 1 neuron model to over-fit a data-set that has its output as one of the input.

**custom prediction** is achieved by code my own function, extract the weights from the model found above, and the result is shown below:

Figure 20)

```
1 print("my prediction: ", my_pre[:10].T)
2 print("model.predict: ", prediction[:10].T)
3 print(["true value: ", YVALID[:10]])
```

my prediction: [[0.52 0.20 0.21 1.00 1.00 1.00 1.00 0.59 0.92 0.96]]  
model.predict: [[0.52 0.20 0.21 1.00 1.00 1.00 1.00 0.59 0.92 0.96]]  
true value: [1.00 0.00 0.00 1.00 1.00 1.00 1.00 1.00 1.00 1.00]

Figure 20: customized prediction result

## 4 Feature importance

**Since there are 6 attributes** in the data set; now, we test the validation set performance after training each attribute alone in the training set.

In section 3, the best model found is 4 layers (NNs 8-4-2-1) with hype-parameter activation "relu", output layer "sigmoid", optimizer "adam", and metrix "accuracy". This model is now being used again with the difference that "input\_dim" = 1, moreover, instead of having all columns except output colum as the input, we will first start with "age", and use this single column to train the training set (predict output in training set), then apply the trained model to predict output in the validation set. Below is the table and bar-chart recorded with all 6 input and their performance in the validation set:

	age	systolicBP	diastolicBP	bloodSugar	bodyTemp	heartRate
LOSS	0.6513	0.5295	0.6199	0.5108	0.6497	0.6714
ACCURACY	0.6040	0.7079	0.6188	0.7228	0.6040	0.6040

Table 12: single attribute prediction performance

Figure 21)

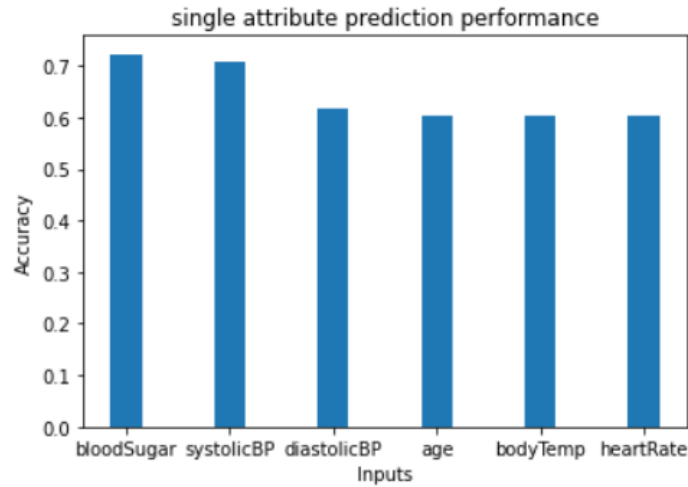


Figure 21: single attribute prediction performance

**As the table and the graph show**, the age, body temperature, and heart rate yield the lowest accuracy which is 0.6040. These data are less importance since they are just passed through the baseline of accuracy, but we will still take them off one by one in the following steps.

The table shown below illustrate the accuracy change after taking each least important input out from the model all the way until the 2 most important feature in the model (see figure 21 for most important feature alone).

	whole model	No age	No age/bt	No age/bt/hr	No age/bt/hr/dBP'
LOSS	0.3994	0.3543	0.4124	0.4312	0.4428
ACCURACY	0.7970	0.8069	0.7772	0.7624	0.7525

Table 13: model performance with decreasing input number

Figure 22)

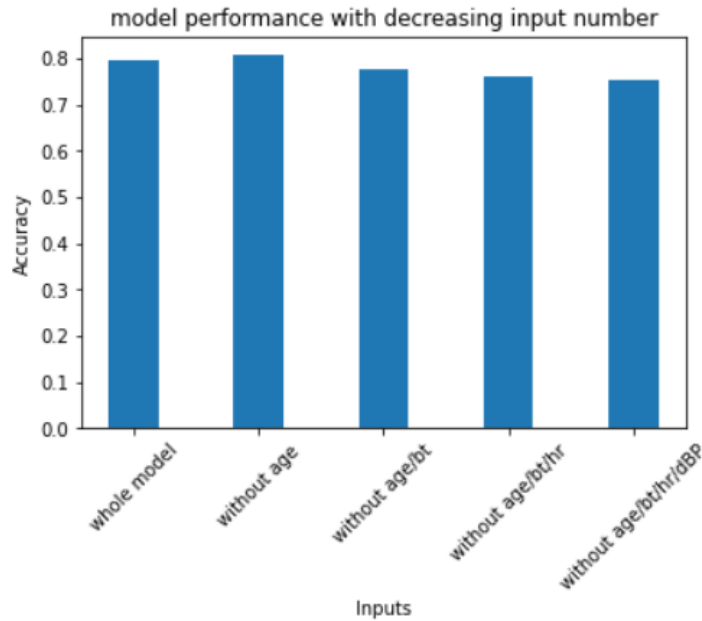


Figure 22: model performance with decreasing input number

**In conclusion,** from figure 21 we can see that blood sugar is the most important input, then systolic blood pressure. In figure 22, we can tell that after remove "age", the accuracy of the model reaches its peak, which is 0.8069. After taking off age we see that even though body temperature and heart rate are also less important compare to others, but the accuracy of the model starts to decrease,



which is, when remove age from data set, the model can best predict whether there is a risk while mothers giving birth according to the data of blood sugar, systolic blood pressure, diastolic blood pressure, body temperature, and heart rate.

## References

- [1] Marzia Ahmed. UCI maternal health risk data set data set, 2020.
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