# Applying neural network method on facial thermal data to predict whether you lie

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**Abstract.** This paper aims to predict lying by using the neural network and facial thermal data. Similar works have been done by using traditional machine learning and facial thermal data. This paper wants to use the neural network and long short-term memory (LSTM) to try to have a better performance. Also, considering the facial thermal data is not stable, the bimodal distribution removal (BDR) method is introduced to try to minimize the noisy data. The best accuracy of neural network reaches 83.3% and the BDR method helps to have a better average accuracy. LSTM method does not perform well maybe due to the contaminated data set. Further performance might be achieved by using larger data or a deeper neural network.

**Keywords:** Neural network, BDR, LSTM, facial thermal data, predict lying

## 1 Introduction

There are various features to show whether you are lying. You might have strange bodily movements, facial expressions, tone of voice, and content of speech [3] (Jalili.C, 2019). But most people are hard to distinguish whether a person is telling lies. Also, you can not find whether a person is lying only by the features of people telling lies. As they might be misleading. For example, you can have strange bodily movements just because you do not feel comfortable. At the same time, however, detecting whether a person is telling lies is important. For example, the airport customs want to know the truths when doing security checks to preventing smuggling [8] (Turri, A., & Turri, J, 2015). In this paper, I will try to address the problem of distinguishing lies in places that need high security by using the thermal data of a person.

Pavlidis and Levine [5] (2002) have shown that facial thermal screening can be helpful to deception detection. Also, neural network like RCNN is good at image classification [2] (Girshick, R. et al, 2014). So, I try to combine those two ideas together. The thermal detection can be performed in security demanding place and the airport customs can predict the results by a well-trained neural network model. Derakhshan, A. et al [1] (2018) detected deceptive by using facial thermal technique with traditional machine learning methods like decision tree and non-linear SVM. However, they did not use the neural network method. The thermal facial data have a large dimension feature. Besides, the connection between features and results is hard to find. The decision tree can not be easily built on high dimension data, and the non-linear SVM needs to use a kernel to map the original data to another form. The kernel would be hard to find when the data have a large dimension. The neural network, however, can find a complex connection between the features and results by using backpropagation. Also, it can deal with multidimensional inputs without difficulty.

As having similar goals, in this paper, I use the facial thermal data collected from Derakhshan, A. et al [1] (2018). The data includes 31 people's facial thermal data when they are lying or telling the truth. The thermal data of each person has been simplified to only 20 features. Derakhshan, A. et al [1] (2018) focused on 5 ROI: periorbital, forehead, cheek, perinasal and chin. They got 20 features by performing the Granger causality on each paired ROI (not having the ROI pair that connects with itself) and gained connectivity between them. The result was encoded as "1" to lying and "0" to telling the truth.

## 2 Method

### 2.1 Preprocessing the data

Since the data has only 31 people, only a shallow neural network can be used to prevent overfitting. Commonly used data augment methods are hard to use, as the data is about the connectivity between the ROI pairs of each person. We can not build the data of a different person. Fortunately, the data results (lying or telling the truth) are balanced. So, no further jobs for balancing the data. Before feeding data to the neural network, I normalize each feature to range 0 to 1 to get a better performing to the training. In this paper, I divide 60% of the data as the training sets, 20% of the data as validating sets, and 20% of the data as the testing sets. As the data set is small, to ensure the data in each set is balanced, stratified sampling is used. The stratified sampling would give almost the same amount of data of each classification class to the data set. In this case, the training set would have 9 data on lying and 10 data on telling the truth. Both the validating set and testing set have 3 data on lying and 3 data on telling the truth.

### 2.2 Neural network

As shown in figure 1, the neural network has 2 hidden layers. The first hidden layer is in $20 \times 7$ dimension and the final hidden layer is in $7 \times 2$ dimension. Each layer is followed by a relu activation function. The network uses Stochastic gradient descent (SGD) as the optimizer with the learning rate at 0.05. Also, to prevent overfitting, early stopping is used during the training.

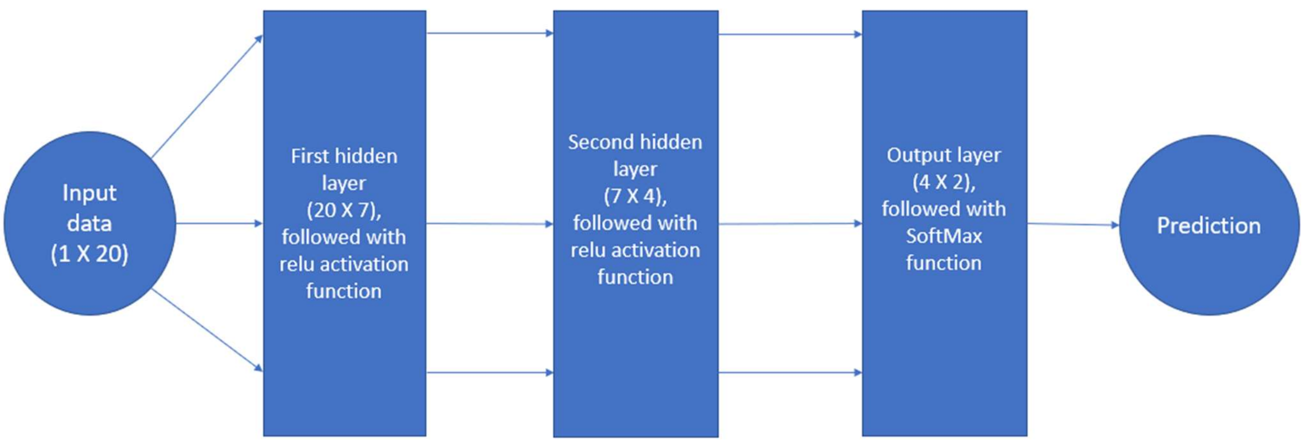


**Fig. 1.** The structure of the neural network. There are two hidden layers. The first one is in 20 X 7 dimension followed with the relu activation. The second is in 7 X 4 dimension. Finally, the output layer is in 4 X 2 dimension with the SoftMax function to predict the result.

### 2.3 Bimodal Distribution Removal

I would use Bimodal Distribution Removal (BDR) method to try to optimize the performance of the neural network. The facial thermal data is full of noise. The data is calculated by the thermal temperature of the ROI. However, the temperature is not stable for every nearby region. So, recording every temperature data would have noise. Also, the tested people were answering questions during the recording of the temperature. The moving mouth would influence the record of the region near the mouth like perinasal and chin. Slade P. and Gedeon T.D. [7] (1993) proposed the BDR method to clean the noisy training data set. Mainly, this method drop part of the "noisy" data after the neural network can learn the outline of the function. After training the normal neural network, I would try to improve the performance by using the BDR method. As the data set is small, I do not drop the data by using the complex criterion used in the origin paper. If I drop much data during the training, I would have even less training data which might cause overfitting. Instead, for each time, I only drop the data that have the largest cross entropy loss. Since the model has learned the outline, the data with the largest loss can be considered as the "noisiest" data.

### 2.4 Long Short-term memory (LSTM)

#### 2.4.1 preprocessing data for LSTM

LSTM [6] (Sepp, H. & Jürgen, S, 1997) uses sequence data as the input for the model, so I use the data set that records the time to time facial thermal data of each participant. In the research of the Derakhshan, A. et al [1] (2018), they asked 8 questions while recording the facial thermal temperature during the whole process. There are 7 questions for the reference samples and 1 question about what we concern. Each question records up to 20 seconds and 10 frames are recorded in every second. The maximum and minimum facial temperatures of 5 ROI are logged for each frame.

From the data set, I extract data that we need and clean the data. Firstly, I extract the data for each participant when our interested question is asked. To ensure the data is highly accurate, I compare those data with the data of the same ROI while other questions are asked. I deleted the data of the participant that is largely different with the reference samples. Secondly, I notice that, mostly the maximum and minimum temperature of same ROI does not different much. However, there is some data where the maximum and minimum temperature is quite different like the maximum temperature is about 33 while the minimum temperature is about 25. Also, there is some data where the temperature of one region changed so rapidly. For example, some participant's temperature drops from 33 to 28 in 0.1 seconds. I think those data might be contaminated by the environment and the actual temperature is not recorded. So, I also delete those data and only the data of the 28 participants remains. Thirdly, from the great results achieved in neural network, I find that whether a person is lying or not can be determined by the temperature of the 5 ROIs. With the fact that the maximum and minimum temperature of same ROI does not different much, I use the average value of the maximum and minimum temperature of each region to represent the temperature of each ROI. Finally, I normalize the data set to make sure each temperature value ranges from 0 to 1.

#### 2.4.2 LSTM

The LSTM is one of the most popular models in among the recurrent neural network (RNN). It enhances the ability of memorizing data by adding more complicated computation above the hidden layer [4] (Junyoung, C et al. 2014). I use the time series of the facial thermal data as the input of the LSTM and the LSTM model can learn the features by the parameters and predict whether the person is lying or not. I consider every 1 second time series of the temperatures are one whole input for the LSTM model. For example, the time series data of the ROI temperatures from 0 second to 1 second are the first input, and the data from 0.1 second to 1.1 second is the second input.

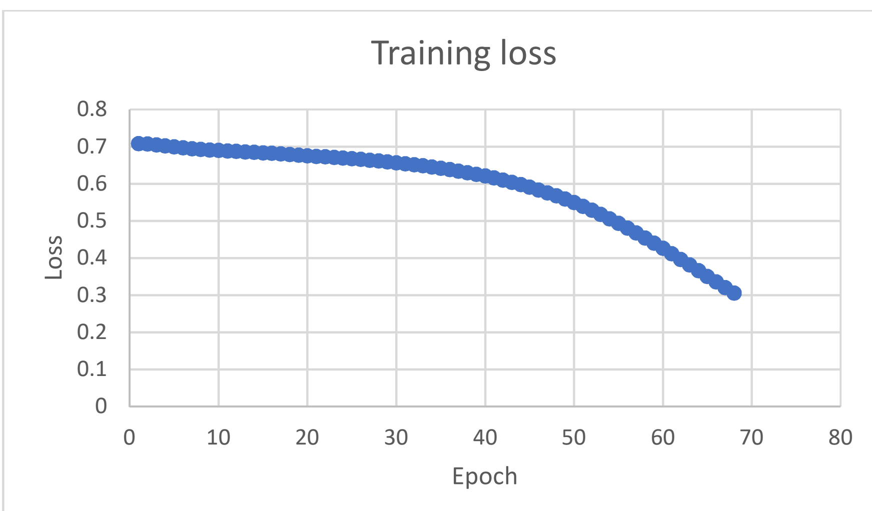


**Fig. 2.** The training loss decease as the epoch increase. Early stopping is applied in epoch 68.

## 3 Results and discussion

### 3.1 Neural network

The neural network performs well in this situation. As shown in figure 2 and 3, the loss of the neural network decreases as the epoch of training increase. The decrease of the training loss means the neural network is learning from the training sets and the decrease of the validating loss means the neural network is not overfitting. The validating loss increases after the epoch 68, so I perform the early stopping. As a result, the accuracy of the training data becomes 100%, the accuracy of the validating data becomes 83.3%, and the test data's accuracy is 83.3%.

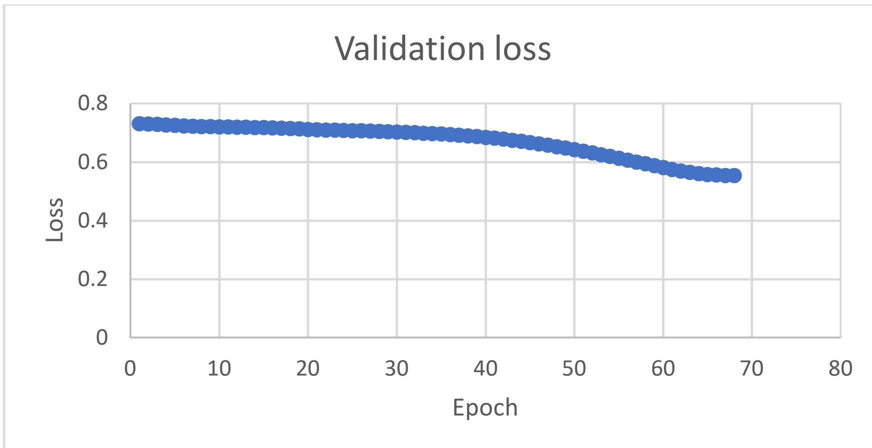


**Fig. 3.** The training loss decease as the epoch increase. Early stopping is applied in epoch 68.

### 3.2 Applying BDR method

The BDR method gets a similar result. As shown in figure 4 and 5, a similar phenomenon is shown. This means the training process is well performed. On epoch 60, we can use see the loss of the training data decreases sharply. It is because the "noisiest" data is removed. The training stops sooner after the epoch 64. The accuracy of all the training set, validation set, and the testing set is 83.3%. However, BDR method is more stable. For training 30 times, the normal method would have 9 times that perform a good training while the BDR method would have 18 times. So, the BDR method has better performance in the average accuracy.

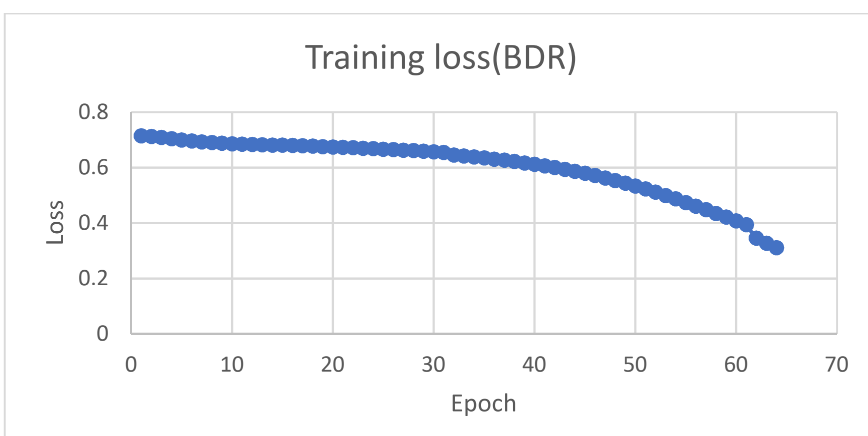


**Fig. 4.** The training loss decease as the epoch increase. There is a sharp decrease in epoch 60, as the noisy data is dropped. Early stopping is applied in epoch 64.

### 3.3 Applying LSTM

The results of the LSTM are frustrating. As the epoch goes up, the training loss tends to go down and the training accuracy goes up. It is to say the model is learning from the training set. However, both the validation accuracy and the test accuracy remain unchanged and equals 58.4%. I have tried for serval times and the results are the same. I find the outputs for the validation sets and test sets are all “1”. It shows that what the model learn does not fit the other data. I separate the data for each person to training, validation and test data sets. So, it means that the data of different time does not all represent the situation. To test whether there is wrong with the hyperparameter, I adjust the value of the learning rate, the time length of the input data and the hidden neural sizes. However, the results are the same as the first model. So, I think maybe the data may not all influence the results and the data of most time is redundant. Those redundant data may influence the learning of the model.

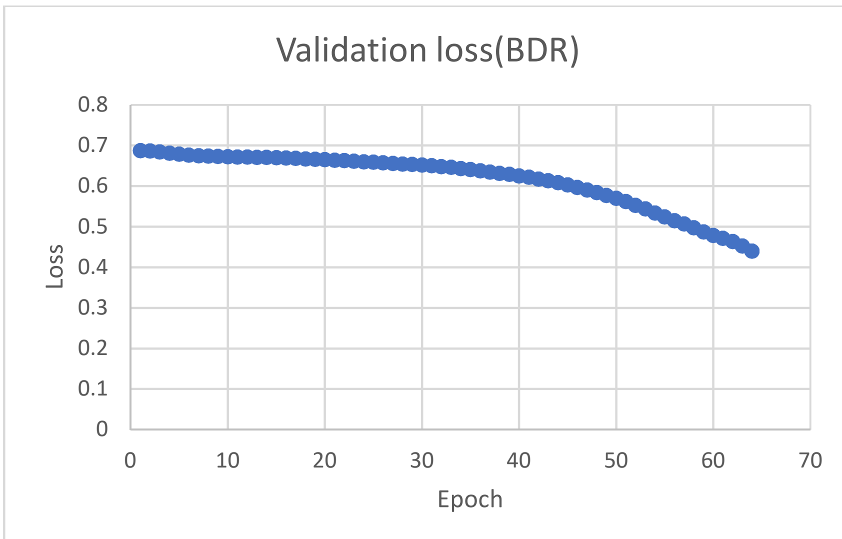


**Fig.5.** The training loss decease as the epoch increase. Early stopping is applied in epoch 68.

### 3.4 Discussion

As shown in table 1, although the performance of the neural network is good, it does not win the results of the traditional machine learning methods by Derakhshan, A. et al [1] (2018). And the BDR method does not help the model have a better performance. The main reason for having not reasonable results might be having too few data sets. The neural network would have a better performance with more data sets. The benefit of using the BDR method might also be limited by the neural network performance. Although the BDR method does not increase the accuracy of the neural network, it helps the network to learn the function correctly. For the training, using the BDR method prone to get the well-trained model. It might because the BDR method removes the “noisiest” data to help the network model not be misled by the noise and get out of the local minimum. LSTM does not perform well and predicting all “1” for the testing set, so the accuracy results are meaningless. One possible method for improving the performance might be taking more data and take the whole data of one participant for the training. Since the LSTM model takes fixed number of inputs, the recording time should be the same. Also, to prevent dirty data influencing the model, the environment temperature and other influence factors need to be controlled.

**Table 1.** Comparison between neural network, neural network using BDR, LSTM, decision tree and non-linear SVM

| Name | Best Accuracy |
| --- | --- |
| **neural network** | **83.3%** |
| **neural network using BDR** | **83.3%** |
| **LSTM** | **58.4%** |
| **Decision tree** | **58.4%** |
| **Non-linear SVM** | **87.1%** |

## 4 Conclusion

The main goal of this study is to try to use the neural network and the facial thermal data to detect whether the person is lying. This paper assumes that there is a relationship between facial thermal data with whether human is lying. And this relationship can be mostly presented by the neural network, the accuracy can reach to 83.3% and the training can be improved by the BDR method. Using BDR method tends to prevent the local minimum. The effect of the neural network is promising. Although the result of the LSTM is not successful, it might be using too little data. Applying the model to the real world is still a long way to go, as the accuracy should be almost 100%.

Further study could be training the neural network with a large data set and training a deeper neural network. Also, we may not use the features extracted from the image. But using the thermal image of the face to be trained directly on the CNN.

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