**A summary for Chapter 1:**

Best models, experiments, and their results on 44 samples

**A summary: we have two best models:**

1. Transfer Learning based Recurrent Neural Networks (RNN) with Long Term Short Memory (LSTM) architecture and Autoencoder for feature selection (TL-LSTM-Autoencoder).
2. Transformer deep learning architecture with Autoencoder for feature selection (Transformer-Autoencoder).

**A brief comparison:**

* Both models make total number of correct predictions = 27/44 (61.36%)
* TL-LSTM-Autoencoder abstains the remaining 17/44 samples in lower values of abstain parameters.
* Transformer-Autoencoder works faster.

**Conclusion:**

Transformer-Autoencoder is better if you don’t have access to another source of data. But, if you do, then TL-LSTM-Autoencoder model may be preferred. Thus, both these models are our best models that work with 100% in all performance metrics in small (but long) CTG data.

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| **Table 1.** All experiments. | | |
|  | **Feature selection** | |
| **Model** | PCA | Autoencoder |
| Transfer Learning based RNN (LSTM) | 47.73% | 61.36% |
| RNN (LSTM) | 45.45% | 56.82% |
| Transformer | 50.00% | 61.36% |
| Random Forest | 45.45% | 59.09% |

Table 1 shows all experiments; models with two different approaches for feature selection. The percentage in this table shows the fraction of 44 samples each corresponding model does not abstain and correctly predicts with 100% in all performance metrics.

There are many other takeaways related to architecture of the models, their properties, and their performances. For example, as you can see, autoencoder usage generally enhances models’ power. The main reason for this is that autoencoder for feature selection (dimensionality reduction) is so fit for time series data. They can capture non-linear features while PCA cannot.

The following pages delve into more details of our two best models. Results of other models from table 1 can be found in the attached spreadsheet document.

# 1. Models and results

## 1.1. TL-LSTM-Autoencoder model (it is a two-part model)

* Part1: RNN (LSTM) model for pretraining on the Public Data (CTU-UHB)
  + Early Stopping Criteria
  + 10 folds Cross Validation
  + Abstain consideration
* Part2: RNN (LSTM) model that uses knowledge from the pretrained model to do overtraining and classification on Shands 44 samples
  + PCA for feature selection.
  + Early Stopping Criteria
  + Leave-one-out Cross Validation
  + Abstain consideration

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| **Table 2.** Results of TL-LSTM-Autoencoder on Shands’ dataset. | | | | | | |
| Fold | Patient | TP (nc) | TN (c) | FP (c but predicted nc) | FN (nc but predicted c) | Abstain threshold |
| 1 | Signal\_10c |  |  |  | 1 | 0.55 |
| 2 | Signal\_13s |  | 1 |  |  |  |
| 3 | Signal\_14c |  |  |  | 1 | 0.6 |
| 4 | Signal\_15c |  |  |  | 1 | 0.55 |
| 5 | Signal\_16s |  | 1 |  |  |  |
| 6 | Signal\_17s |  | 1 |  |  |  |
| 7 | Signal\_18c | 1 |  |  |  |  |
| 8 | Signal\_20s |  | 1 |  |  |  |
| 9 | Signal\_21s |  |  | 1 |  | 0.65 |
| 10 | Signal\_23c | 1 |  |  |  |  |
| 11 | Signal\_25s |  | 1 |  |  |  |
| 12 | Signal\_26c | 1 |  |  |  |  |
| 13 | Signal\_27c | 1 |  |  |  |  |
| 14 | Signal\_28s |  | 1 |  |  |  |
| 15 | Signal\_30s |  |  | 1 |  | 0.75 |
| 16 | Signal\_34s |  |  | 1 |  | 0.55 |
| 17 | Signal\_35c | 1 |  |  |  |  |
| 18 | Signal\_36c |  |  |  | 1 | 0.55 |
| 19 | Signal\_37c | 1 |  |  |  |  |
| 20 | Signal\_39s |  | 1 |  |  |  |
| 21 | Signal\_3c | 1 |  |  |  |  |
| 22 | Signal\_40s |  | 1 |  |  |  |
| 23 | Signal\_41c | 1 |  |  |  |  |
| 24 | Signal\_42c | 1 |  |  |  |  |
| 25 | Signal\_43s |  | 1 |  |  |  |
| 26 | Signal\_44s |  | 1 |  |  |  |
| 27 | Signal\_45s |  |  | 1 |  | 0.7 |
| 28 | Signal\_46s |  | 1 |  |  |  |
| 29 | Signal\_47s |  | 1 |  |  |  |
| 30 | Signal\_48s |  |  | 1 |  | 0.6 |
| 31 | Signal\_49s |  | 1 |  |  |  |
| 32 | Signal\_50s |  | 1 |  |  |  |
| 33 | Signal\_53s |  |  | 1 |  | 0.55 |
| 34 | Signal\_54c |  |  |  | 1 | 0.9 |
| 35 | Signal\_55c | 1 |  |  |  |  |
| 36 | Signal\_56c |  |  |  | 1 | 0.55 |
| 37 | Signal\_57c | 1 |  |  |  |  |
| 38 | Signal\_58c |  |  |  | 1 | 0.7 |
| 39 | Signal\_59c |  |  |  | 1 | 0.6 |
| 40 | Signal\_5s |  | 1 |  |  |  |
| 41 | Signal\_61c |  |  |  | 1 | 0.55 |
| 42 | Signal\_62c |  |  |  | 1 | 0.55 |
| 43 | Signal\_6c |  |  |  | 1 | 0.55 |
| 44 | Signal\_7s |  | 1 |  |  |  |
| Sum | | 27 | | 17 | |  |
| Percentage | | 38.64% | | 61.36% | |  |

## 1.2. Transformer-Autoencoder model

* + Autoencoder for feature selection
  + Early Stopping Criteria
  + Leave-one-out Cross Validation
  + Abstain consideration

Transformer architectures in Deep Learning (DL) are particularly suitable for long signal data like Fetal Heart Rate (FHR) traces because they excel at capturing complex, long-range dependencies within the entire data. Their self-attention mechanism allows them to focus on important patterns across the entire sequence without being constrained by the sequential processing limitations of RNNs, making them highly effective for accurately classifying time-dependent biomedical signals such as BPM.

In addition, Autoencoder is generally more efficient for feature selection of signal time series data due to its ability to capture non-linear relationships.

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| **Table 3.** Results of Transformer-Autoencoder model on Shands’ dataset. | | | | | | |
| Fold | Patient | TP (nc) | TN (c) | FP (c but predicted nc) | FN (nc but predicted c) | Abstain threshold |
| 1 | Signal\_10c |  |  |  | 1 | 0.6 |
| 2 | Signal\_13s |  | 1 |  |  |  |
| 3 | Signal\_14c |  |  |  | 1 | 0.65 |
| 4 | Signal\_15c | 1 |  |  |  |  |
| 5 | Signal\_16s |  | 1 |  |  |  |
| 6 | Signal\_17s |  | 1 |  |  |  |
| 7 | Signal\_18c | 1 |  |  |  |  |
| 8 | Signal\_20s |  | 1 |  |  |  |
| 9 | Signal\_21s |  |  | 1 |  | 0.7 |
| 10 | Signal\_23c | 1 |  |  |  |  |
| 11 | Signal\_25s |  | 1 |  |  |  |
| 12 | Signal\_26c | 1 |  |  |  |  |
| 13 | Signal\_27c | 1 |  |  |  |  |
| 14 | Signal\_28s |  |  | 1 |  | 0.55 |
| 15 | Signal\_30s |  |  | 1 |  | 0.95 |
| 16 | Signal\_34s |  |  | 1 |  | 0.6 |
| 17 | Signal\_35c | 1 |  |  |  |  |
| 18 | Signal\_36c |  |  |  | 1 | 0.55 |
| 19 | Signal\_37c | 1 |  |  |  |  |
| 20 | Signal\_39s |  | 1 |  |  |  |
| 21 | Signal\_3c | 1 |  |  |  |  |
| 22 | Signal\_40s |  | 1 |  |  |  |
| 23 | Signal\_41c | 1 |  |  |  |  |
| 24 | Signal\_42c | 1 |  |  |  |  |
| 25 | Signal\_43s |  | 1 |  |  |  |
| 26 | Signal\_44s |  | 1 |  |  |  |
| 27 | Signal\_45s |  |  | 1 |  | 0.7 |
| 28 | Signal\_46s |  | 1 |  |  |  |
| 29 | Signal\_47s |  | 1 |  |  |  |
| 30 | Signal\_48s |  |  | 1 |  | 0.6 |
| 31 | Signal\_49s |  | 1 |  |  |  |
| 32 | Signal\_50s |  | 1 |  |  |  |
| 33 | Signal\_53s |  |  | 1 |  | 0.6 |
| 34 | Signal\_54c |  |  |  | 1 | 0.95 |
| 35 | Signal\_55c | 1 |  |  |  |  |
| 36 | Signal\_56c |  |  |  | 1 | 0.6 |
| 37 | Signal\_57c | 1 |  |  |  |  |
| 38 | Signal\_58c |  |  |  | 1 | 0.75 |
| 39 | Signal\_59c |  |  |  | 1 | 0.6 |
| 40 | Signal\_5s |  | 1 |  |  |  |
| 41 | Signal\_61c |  |  |  | 1 | 0.55 |
| 42 | Signal\_62c |  |  |  | 1 | 0.6 |
| 43 | Signal\_6c |  |  |  | 1 | 0.65 |
| 44 | Signal\_7s |  | 1 |  |  |  |
| Sum | | 12 | 15 | 7 | 10 |  |
| Percentage | | 61.38% | | 38.64% | |  |