Contrastive Predictive Coding for anomaly detection of fetal health from the cardiotocogram

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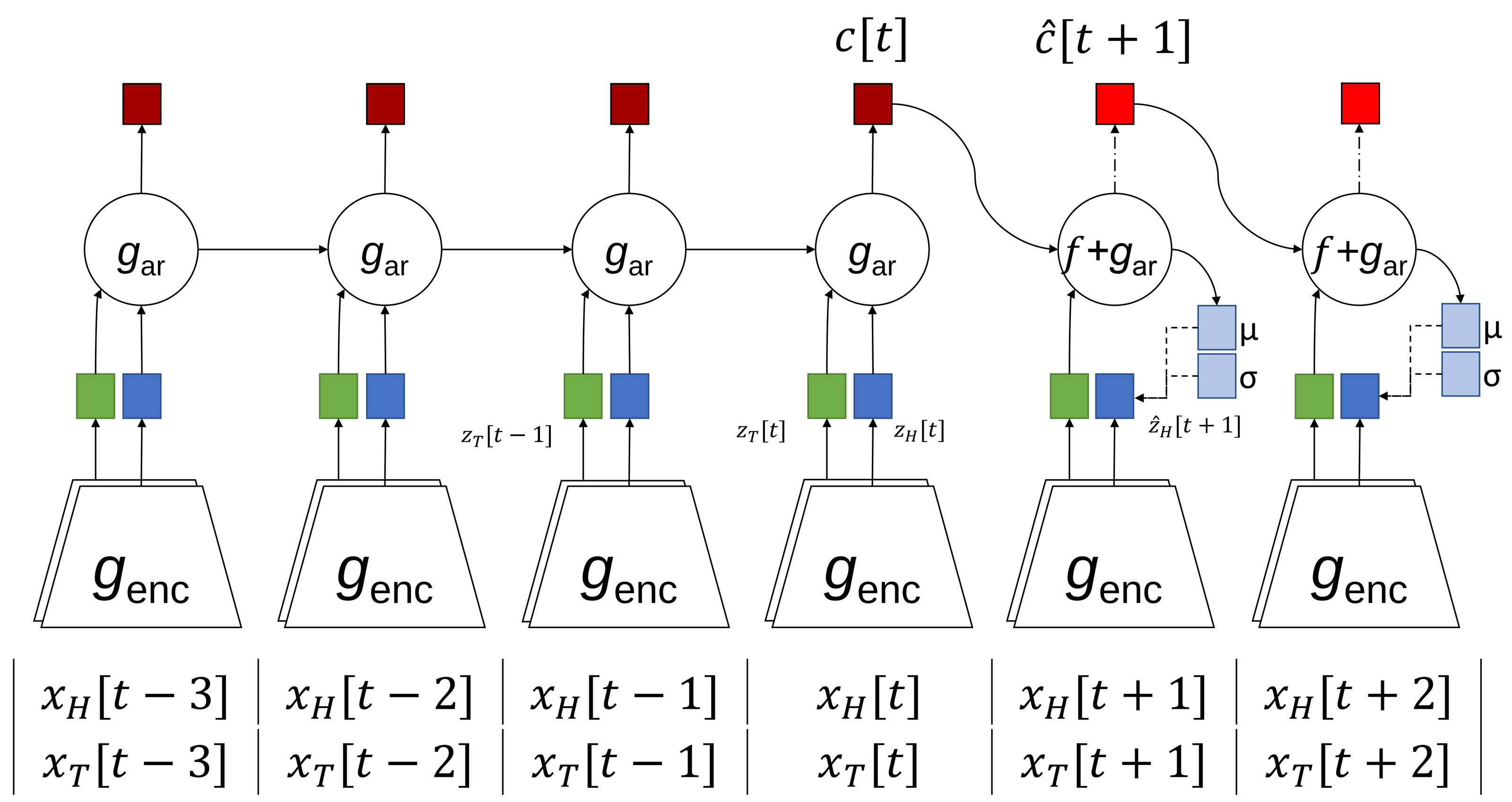
PROBLEM DEFINITION

- ✓ **Clinical challenge:** interpretation of fetal health from simultaneous measurements of fetal heart rate and uterine activity during labor.
- ✓ **Current approach:** Visual inspection of cardiotocogram by medical experts.
- ✓ **Hypothesis:** Unsupervised training on healthy measurements provides a framework for anomaly detection of fetal health.
- ✓ **Goal:** An objective method for the real-time identification of anomalies in fetal health, useable for clinical decision support.
- ✓ **Method:** An adapted CPC model [1] trained on healthy data detects an absence of healthy features or an abnormal change in the fetal cardiac recording (FHR), conditioned upon the uterine contractions (toco).

ADAPTED CPC FRAMEWORK



- ✓ Cardiac prediction conditioned upon uterine contractions
- ✓ Recurrent predictor network
- ✓ Sampling module during training

CUSTOM TRAINING LOSS

For K future windows, loss $L[t]$ is given by

$$L[t] = \frac{1}{K}\sum_{k=1}^{K}\left(L_{sim}[t+k] + L_{contr}[t+k]\right)$$

with

$$L_{sim}[t] = 1 - cosSim(\hat{\mathbf{z}}_H[t], \mathbf{z}^+[t])$$

and

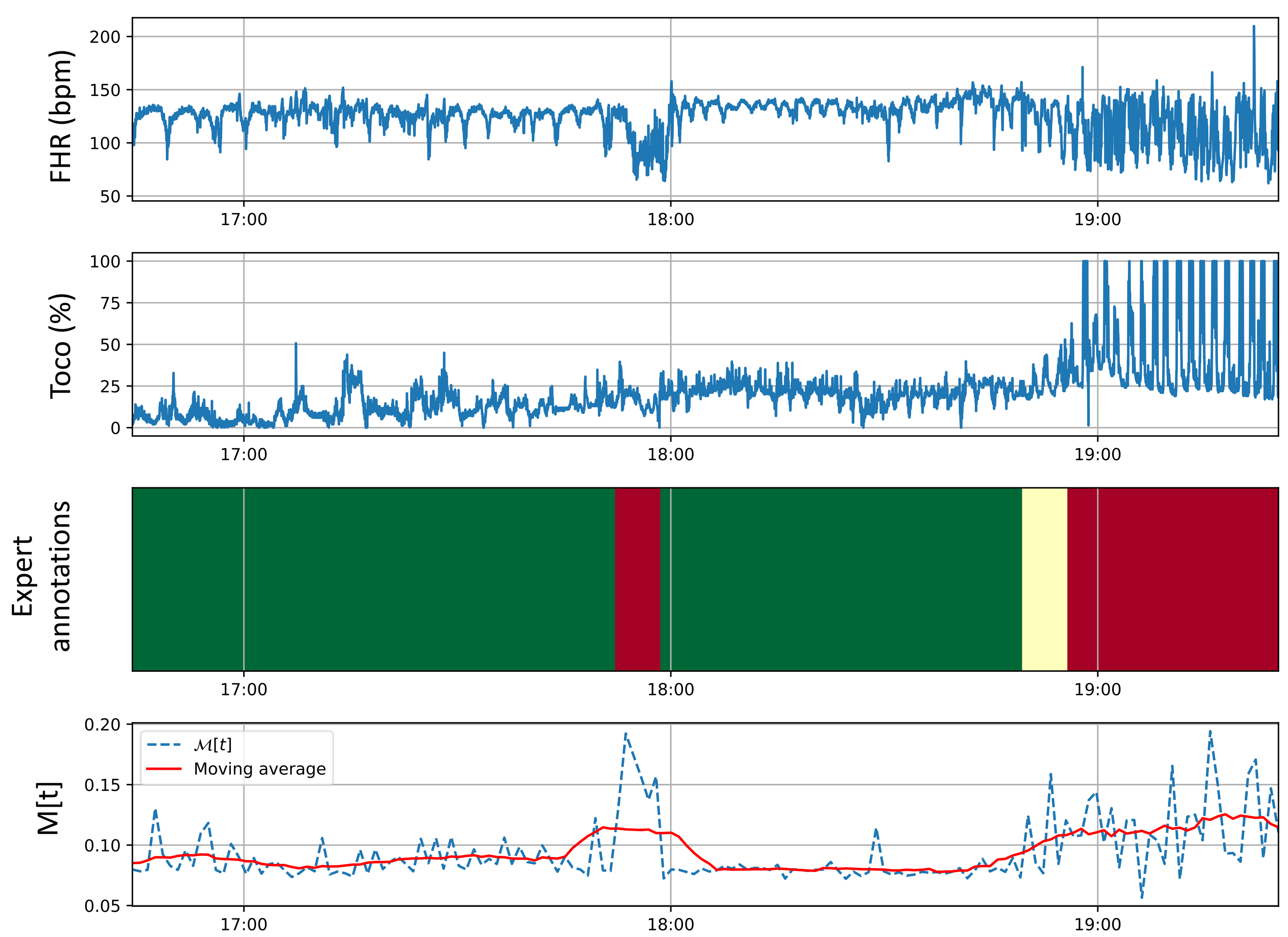
$$L_{contr}[t] = \max(0, MSE(\hat{\mathbf{z}}_H[t], \mathbf{z}^+[t]) - \min_{\mathbf{z}^- \in Z_H^-[t]}(\hat{\mathbf{z}}_H[t], \mathbf{z}^-))$$

L_{contr} is used to prevent trivial solutions, drops out when the MSE for the negative samples exceeds the MSE for the positive samples.

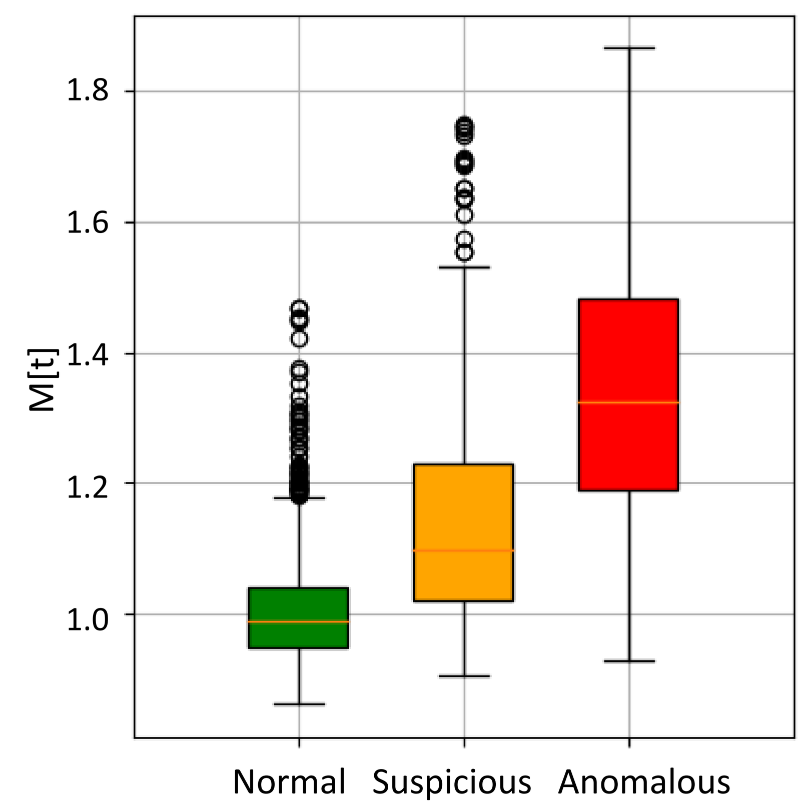
ANOMALY SCORE

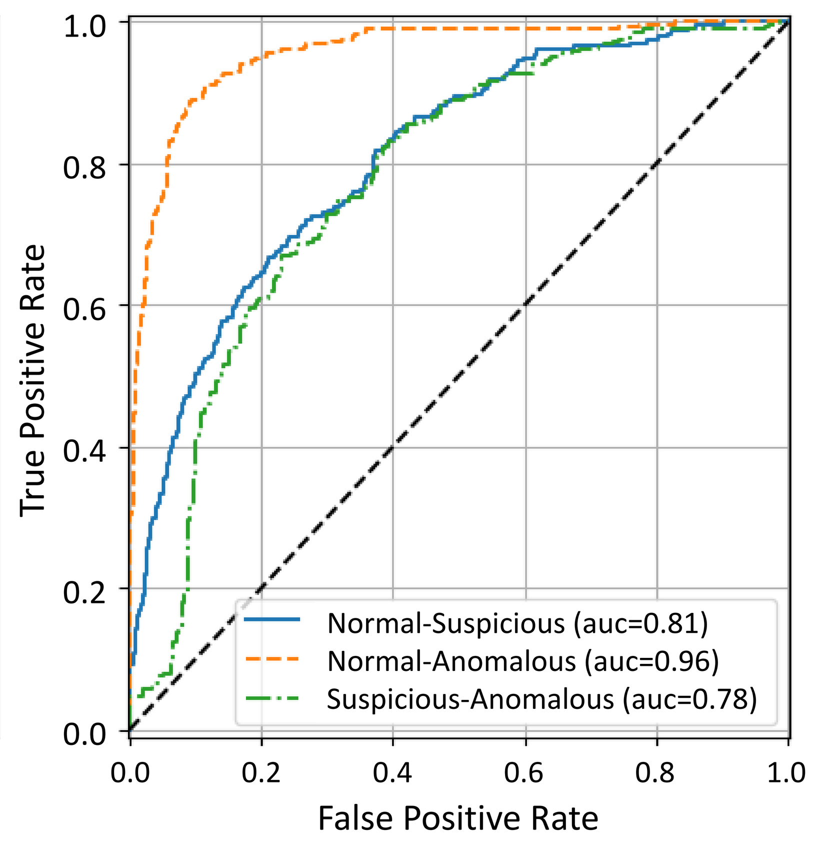
- ✓ Model trained on healthy data
- ✓ Child's toco-FHR interaction modeled in conditional prediction
- ✓ Minute-to-minute scoring achieved by 1-minute windows

Average MAE for future predictions used as anomaly metric M[t]



RESULTS





Results are presented for the 10-window moving average of model output and grouped according to expert labels.

Combining the data for six measurements with a healthy outcome gives a correlation of 0.70 between model output and expert labels.

ROC-curves yield AUC values ≥ 0.78 for distinctions between normal, suspicious and anomalous events.

AUC = 0.96 for the most important distinction between normal and anomalous events.

FUTURE WORK

Evaluation should be done on a bigger dataset annotated by multiple medical experts and should include measurements with an unhealthy outcome as well.

REFERENCES

[1] Oord *et al.* (2018). Representation learning with contrastive predictive coding.