Machine learning in medicine

Appendix A

Summary

A.1 Machine learning in medicine

Machine learning models can outperform clinicians both in accuracy and speed and do not suffer from emotion-based decision making or fatigue. Despite the high potential of machine learning models for clinical application, actual clinical implementation is much lower. This discrepancy may be due to several reasons, amongst others the trust and reliance of clinicians in the particular model. Several factors may affect model accuracy and clinicians' trust.

The aim of this thesis was to analyse the importance of three small but crucial steps inherent to model creation and implementation in medicine. First, we addressed the importance of raw data assessment. Second, we identified the need for adequate and physiology-based parameter extraction. Third, we evaluated the importance of model selection.

A.2 Raw data assessment

In Chapter 2 we exemplified the importance of raw data assessment in pulse transit time (PTT) measurements, i.e. in the estimations of the delay between the R peak in the ECG and the upslope in the plethysmogram. In patients and in simulations, a constant increase in PTT followed by a sudden decrease after a set time interval was observed. This behaviour of PTT was the result of minimal prolongation of each plethysmogram waveform followed by an abrupt shortened single wave. Since the ECG did not exhibit this pattern, the prolongation and sudden shortening of the plethysmogram waveform resulted in a sawtooth artifact. Although PTT is a commonly used clinical parameter, the sawtooth artifact is large enough to prevent clinical usefulness. Our finding emphasizes the need for continuous data quality monitoring because clinically accepted parameters may still contain severe artifacts.

A.3 Parameter extraction

Parameter quality is of the utmost importance for model accuracy. High quality parameters can be developed using knowledge of the underlying physiology. We exemplified the need for adequate and physiology-based parameters in Chapter 3 by developing a parameter that can discriminate between preterm infants with or without a patent ductus arteriosus. The ductus arteriosus is a connecting vessel between the aortic arch and the pulmonary artery that should close after birth. If the ductus arteriosus does not close after birth, which often occurs in preterm infants, it is called a patent ductus arteriosus. Due to the positive pressure difference between the aorta and the pulmonary artery, a patent ductus arteriosus shunts blood from the systemic to the pulmonary circulation and, hence, may influence systemic blood pressure. Based on this knowledge, we hypothesized that the ratio of the upward - and downward slope arterial blood pressure at the borders of a given window surrounding the systolic peak can discriminate between patients with and without a patent ductus arteriosus. Our proposed parameter predicted the presence of a patent ductus arteriosus in preterm infants with an accuracy of 83.3%. We conclude that development of high-quality physiology-based parameters is important to improve clinical model accuracy.

A.4 Model creation

The outcome in severe traumatic brain injury patients admitted to the intensive care unit ranges from full recovery to death. It is helpful for medical personnel to know in advance how well a patient may recover, as this may indicate how aggressive the patient should be treated. In Chapter 4 we created a logistic regression model to predict whether a severe traumatic brain injury patient admitted to the intensive care unit has a favourable or unfavourable outcome after six months. The prediction was based on physiology-based parameters measured during the first six hours after admission. These parameters were shown or suspected to be indicative of the outcome. The logistic regression model was able to obtain a prediction accuracy of 86.7%. The high accuracy obtained indicates that a simple linear model may be sufficient to accurately predict the outcome in heterogenous groups like severe traumatic brain injury patients. The transparency of the logistic regression model enables the clinician to assess the importance of individual parameters according to their clinical reasoning. Due to the high prediction accuracy, high interpretability and logical reasoning of the model, clinicians may trust and implement this model in their practice. We conclude that models can be accurate and simple at the same time, resulting in a clinically useful model that can be implemented and trusted by clinicians.

Although simple models such as logistic regression models can result in accurate predictions, some clinical problems do require a more sophisticated approach. One of such clinical problems is the detection of pending cerebral hypovolemia due to progressive central hypovolemia, for instance due to bleeding during surgery. In Chapter 5 and 6 we induced central hypovolemia in healthy volunteers up to the point of cerebral hypovolemia as shown by symptoms of syncope. A neural network and a support vector machine were used to predict on a beat-to-beat base how far a subject was from cerebral hypovolemia. It was found that impending syncope could be fairly accurately estimated using these two models that implemented a variety of continuously measured parameters. However, due to the nature of these models, interpretability was low. Therefore, the model and the prediction are interesting, but clinical implementation may lag behind due to the fact that the clinician cannot understand and evaluate the reasoning of the model. We conclude that not only model accuracy, but also model interpretability, transparency and possible implementation should be leading indicators for model selection.

This thesis ends with a general discussion in Chapter 7 in which the various chapters are put into a broader perspective.

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