Abstract Title: Prediction of Neonatal Hypoglycemia Risk from Maternal Continuous Glucose Monitoring Data Using Transfer Learning

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Neonatal hypoglycemia is a major complication in infants born to diabetic mothers. Hypoglycemia in neonates can cause neuronal injury and result in neurodevelopmental morbidities. The available data consisted of a 1-dimensional timeseries of maternal glucose readings every 5 minutes during pregnancy via continuous glucose monitoring (CGM) from a retrospective single-site study of mother-infant pairs monitored using CGM during prenatal care at the University of Alabama at Birmingham (UAB) from 9/1/2018 to 3/31/2022. The primary outcome was neonatal hypoglycemia, defined by serum/point of care glucose measurement of <40 mg/dl in the first 24 hours after birth. The study hypothesis was that a deep learning model with transfer learning could identify neonates at risk of hypoglycemia using maternal CGM data with good predictive ability (area under the receiver operating characteristic curve, AUC-ROC >0.70).

Given a small sample size (n=90), we employed a transfer learning [1,2] artificial intelligence (AI) framework to assign probabilities of the primary outcome using maternal CGM data. Searching for publicly available models trained on 1-dimensional sequence data led us to a convolutional neural network (CNN) [3] trained on the "FordA" dataset available from the UCR (University of California Riverside) archive [4]. We acquired the pretrained network from a Hugging Face repository [5] in a TensorFlow 2 implementation [6].

Model importing with pre-trained weight plus parameters and (re)training was conducted in Matlab 2022b using the Deep Learning Toolbox, which includes functions for importing trained TensorFlow models. For training with the UAB data set, the model input was the 1-dimensional CGM data for each mother with neonatal hypoglycemia as the binary target variable. During retraining, the "Weight Learn Rate Factor" and "Bias Learn Rate Factor" of the network's last fully connected layer were set to 10 times that of all others, so that retraining would change this layer significantly more than any of the other pretrained layers.

The predictive ability of the model was assessed using the AUC-ROC, as this was a relatively balanced data set (44% in the positive – hypoglycemic neonate – class) with probabilities (rather than strict classification) being the desired output. For this feasibility study, understanding the ability of the model (re)training pipeline rather than a particular set of final model parameters and weights was judged most important. Therefore, we optimized model training parameters using a Bayesian parameter search and ran multiple training and testing cycles of this model using 5-fold cross validation (CV). The optimal training parameters resulted in a model with average CV AUC-ROC of 0.72 (95% confidence interval of 0.53 to 0.91), meeting our initial criteria for a successful feasibility study.

Predicted neonatal hypoglycemia at or before birth may lead to better infant outcomes via enhanced (and better allocated) monitoring and testing enabled by model predictions such as ours. Having proved the feasibility of our model-building pipeline, a prospective collection of more patient data for model training is underway. Future work will incorporate basic patient demographics and medical history on a larger patient population.

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