Using Interpretable Machine Learning to Predict Maternal and Fetal Outcomes

Tomas M. Bosschieter
tomasbos@stanford.edu
Stanford University
Stanford, CA, USA

Zifei Xu
zifei98@stanford.edu
Stanford University
Stanford, CA, USA

Benjamin J. Lengerich
blengeri@mit.edu
Massachusetts Institute of Technology
Cambridge, MA, USA

Harsha Nori
hanori@microsoft.com
Microsoft Research
Redmond, WA, USA

Vivienne Souter, MD
vsouter@qualityhealth.org
Foundation for Health Care Quality
Seattle, WA, USA

Rich Caruana
rcaruana@microsoft.com
Microsoft Research
Redmond, WA, USA

Hui Lan
huilan@stanford.edu
Stanford University
Stanford, CA, USA

Kristin Sitcov
ksitcov@qualityhealth.org
Foundation for Health Care Quality
Seattle, WA, USA

ABSTRACT

Most pregnancies result in a good outcome, but complications are not uncommon and when they do occur, they can be associated with serious implications for mothers and babies. Predictive modeling has the potential to improve outcomes through better understanding of risk factors, heightened surveillance for high risk patients, and more timely and appropriate interventions, thereby helping obstetricians deliver better care. For three types of complications we identify and study the most important risk factors using Explainable Boosting Machine (EBM), a glass box model, in order to gain intelligibility: (i) severe maternal morbidity (SMM), (ii) shoulder dystocia, and (iii) preterm preeclampsia. While using the interpretability of EBM’s to reveal surprising insights into the features contributing to risk, our experiments show EBMs match the accuracy of other black-box ML methods such as deep neural nets and random forests.

CCS CONCEPTS

• Applied computing → Health informatics; • Computing methodologies → Machine learning.

KEYWORDS

Explainability, intelligible models, generalized additive models, AI for healthcare, obstetrics

1 INTRODUCTION

Of the 3.6 million births per year in the U.S. [24], Severe Maternal Morbidity (SMM) happens in as many as 60,000 cases [9], leading to serious short- or long-term consequences for the mother’s health. In our study, SMM is a composite term for 6 adverse diagnoses: (i) hysterectomy, (ii) blood transfusion, (iii) disseminated intravascular coagulation, (iv) amniotic fluid embolism, (v) thromboembolism, and (vi) eclampsia. Additionally, shoulder dystocia and (preterm) preeclampsia are two other relatively common, serious conditions. If there were a timely risk indication, many cases of SMM, shoulder dystocia and (preterm) preeclampsia could potentially be avoided [8, 9]. While several analyses and black-box models have been deployed to predict SMM and its risk factors [4, 6, 12], preeclampsia [2, 15, 22], and shoulder dystocia [1, 27], the risk factors for each have remained under-studied. Additionally, models trained on international data (e.g. [26]) might not perform as well in U.S.-based hospitals [29].

Equipped with recent clinical data containing 408 features and 222,001 de-identified patients, we use interpretable machine learning models – Explainable Boosting Machines (EBMs) – to uncover the most important risk factors. We show that EBMs yield an Area Under the Receiver Operating Characteristic curve (AUROC) on par with XGBoost [7], random forests [3], deep neural networks (DNNs) [13], and logistic regression [17] while remaining fully interpretable.

Our main contributions are:

• Showcasing how intelligible models reveal surprising risk contribution relationships not traditionally recognized.
• Illustrating EBM’s potential for healthcare applications, rivaling the current industry-standard in obstetrics, logistic regression [25], by outperforming it while also providing intelligibility.
• Leveraging a new and robust data set in healthcare.

2 PRELIMINARIES

For a target variable Y and predictor features \( x_1, \ldots, x_n \), Generalized Additive Models (GAMs) [14] generalize linear (regression) models

\[
Y = \beta_0 + a_1 x_1 + \cdots + a_n x_n
\]

to an additive model with univariate shape functions \( f_i \) and a situation-dependent link function \( g \) (e.g. logistic for classification and identity for regression):

\[
g(\mathbb{E}[Y]) = \beta_0 + f_1(x_1) + f_2(x_2) + \cdots + f_n(x_n)
\]

Explainable Boosting Machines emerge when the \( f_i \) are learned by boosting shallow decision trees in a round-robin fashion [19, 23]. Additionally, EBMs can be trained to automatically detect important pairwise interaction terms to further boost accuracy while preserving intelligibility [20]. Because EBMs are GAMs, all decision
trees for the $i$-th feature are added to generate the shape function $f_i$ and corresponding graph, which displays the $i$-th feature’s effect on the target outcome. EBMs have recently gained popularity because of their local and global interpretability, from applications in healthcare [30] to predicting sports outcomes [10, 28], slope failures [21], and modeling dark matter [5].

3 EXPERIMENTAL SETUP AND METHODS

3.0.1 Data set. The real-world, clinical data used in this analysis are from the Foundation for Health Care Quality’s Obstetrical Care Outcomes Assessment Program (OB COAP) [11], including de-identified patient-level information from medical records at 20 hospitals collected for quality improvement purposes. Out of the 222,001 patients, 3102 (1.40%) had SMM, 4908 (2.21%) shoulder dystocia, and 4555 (2.05%) preterm preeclampsia.

3.0.2 Data analysis. For each outcome, we use clinical expertise to identify and select the features that can be measured before the outcome occurs (with one exception: the shoulder dystocia model includes birthweight, a feature that can only be estimated before birth). We select those features, and do not use the other features to train any of the machine learning models. For example, in trying to predict preterm preeclampsia (i.e. preeclampsia before 37 weeks’ gestation)\(^3\), the feature ‘length of time from hospital admission to delivery’ should not be used by a machine learning model, since labor has not taken place yet and so it’s not known at the time of prediction, namely < 37 weeks’ gestation. However, ‘length of time from hospital admission to delivery’ is selected as a feature to be used in predicting shoulder dystocia and SMM which occur at or after birth.

To obtain training and test data sets, we stratify by hospital, and select a subset of hospitals such that the union of their patients represents 75% of all patients. We use these patients for training, and the other 25% are used as test data for validation. This is a form of external cross-validation, since some hospitals and all their patients are used for training, while a distinct other group of hospitals are used for validation. External validation is standard practice in medical sciences [16, 18]. Furthermore, we use the standard procedure of dummy encoding for categorical data, and impute missing values with the mean. No data normalization is required.

Lastly, as a preprocessing step, we discard birth events with missing values with the mean. No data normalization is required. For example, we never include births with a negative length of time from admission till delivery, births where the baby’s birthweight is over 8000 grams, and cases where the pregnant patient has a BMI over 120 kg/m\(^2\).

3.1 Model parameters

For EBMs, we use hyperparameters outer_bags=25, inner_bags=25, min_samples_leaf=25, interactions=20. For XGBoost we use $\eta=0.04$, subsample=0.7, and max_depth=5. Random forests are trained with n_estimators=1000, min_samples_split=60, and min_samples_leaf=40. Lastly, the DNN is an MLP with 7 hidden

layers of 200 neurons each. The hyperparameters of all models were each determined using 5-fold Cross-Validation to maximize AUROCs while ensuring good calibration and using heuristic methods to minimize overfitting; all parameters not mentioned are common defaults. We use 5-fold CV for all models to make computations feasible.

4 RESULTS

For each outcome (SMM, shoulder dystocia, preterm preeclampsia) we compare EBMs to XGBoost, random forests, deep neural networks in the form of a multilayer perceptron, and logistic regression. The Area Under the ROC curve (AUROC) for each model and outcome can be found in Table 1. The calibration plot for shoulder dystocia is shown in Figure 1b. We exclude the calibration plots of random forests and deep neural networks to allow for close inspection of the graph – they achieve similar calibrations. Similar calibrations are achieved for other outcomes as well.

EBMs allow each feature’s contribution to risk to be easily visualized. Figures 1a, 2a, 2b show two shape functions for each outcome. Observe that the error bars shown in the shape functions in Figures 1a, 2a, 2b represent the standard deviations yielded by the outer-bagging process employed by EBMs.

Furthermore, Figure 3 shows the risk contribution of race and ethnicity for shoulder dystocia and SMM. We see a clinically surprising near-linear relationship between baby weight and risk in Figure 1a for weights between 3250g and 4250g. Using the metric of the mean absolute contribution to log-odds, the most important risk factors for each outcome are ordered in Table 2.

5 DISCUSSION

As shown in Table 1 and Figure 1b, we see that EBMs are well-calibrated models with an AUROC on par with other models. Surprisingly, EBMs find that the biggest contributors to risk aren’t necessarily the traditionally recognized ones. The risk factors usually associated with shoulder dystocia are diabetes and the baby’s birthweight. While the EBM reiterates the great influence of birthweight, it also shows that time from rupture of the membranes to delivery, and the mother’s height are of similar importance. Similarly, the main indicators picked up by the EBM for SMM are preeclampsia/gestational hypertension, time from full cervical dilation to delivery, and c-section, while baby weight and gestational age at delivery also play major roles, but maternal age, race, and ethnicity appear not to be as important predictors. Note, however, that the apparent effects of race are often embedded in other correlated factors like the level of accessible care. Lastly, the largest contributions to the risk of preterm preeclampsia are made by the mother’s BMI, number of previous stillbirths, and pre-pregnancy hypertension, while the mother’s age also plays a major role, especially for women older than 44; see Figure 2a. The comparison to SMM regarding the risk contribution of the mother’s age is noteworthy; see Figure 2b. The contribution of race and ethnicity is shown in Figure 3. Both figures suggest non-White race and Hispanic/Latino ethnicity are associated with higher risks for both shoulder dystocia and SMM.

\(^3\)Note that predicting preterm preeclampsia can only be done in practice < 37 weeks into the pregnancy.
Table 1: A comparison between the Area Under the ROC curve (AUROC) for each outcome. Higher is better.

| Outcome               | EBM     | Logistic Regression | XGBoost  | Random Forests | DNN     |
|-----------------------|---------|---------------------|----------|----------------|---------|
| SMM                   | 0.756 ± 0.020 | 0.748 ± 0.022 | 0.761 ± 0.019 | 0.761 ± 0.018 | 0.742 ± 0.016 |
| Shoulder dystocia     | 0.744 ± 0.017 | 0.744 ± 0.020 | 0.751 ± 0.018 | 0.713 ± 0.019 | 0.752 ± 0.019 |
| Preterm preeclampsia  | 0.770 ± 0.006 | 0.750 ± 0.022 | 0.767 ± 0.018 | 0.749 ± 0.019 | 0.758 ± 0.014 |
| Mean AUROC            | 0.757 ± 0.014 | 0.747 ± 0.021 | 0.760 ± 0.055 | 0.741 ± 0.019 | 0.751 ± 0.016 |

(a) The individual contributions of baby weight and maternal height to the risk of shoulder dystocia.

Figure 1: Along with a calibration plot, we show two shape functions for shoulder dystocia: the risk contribution of (i) baby weight, and (ii) the mother’s height. Similar calibration is achieved for other models, which are omitted to allow for detailed inspection.

Table 2: The three most important contributors to the risk for each outcome according to the EBM.

| Rank | SMM                      | Shoulder dystocia                        | Preterm preeclampsia                      |
|------|--------------------------|------------------------------------------|-------------------------------------------|
| 1    | Preeclampsia/gestational hypertension | Baby’s weight                           | Mother’s BMI                              |
| 2    | Time full cervical dilation to delivery | Time membranes rupture till delivery     | Num. previous Stillbirths                 |
| 3    | C-section                | Mother’s height                          | Pre-pregnancy hypertension                |

The perceived jumps in Figure 1a, and other contribution graphs as well, are likely due to clinical interventions happening at clinically relevant cut-offs. Figure 1a uses actual birth weight (as opposed to estimated birth weight) to highlight the importance of fetal weight for shoulder dystocia. This alludes to the value more research and improved estimates of prenatatal weight could play in predicting maternal and fetal outcomes. Additionally, in light of the importance of a mother’s height to the risk of shoulder dystocia, we propose including pelvimetry in clinical examinations, reiterating the relationship between the mother’s height and pelvic opening.

6 CONCLUSIONS
We leverage a new, robust data set together with the intelligibility of EBMs to illustrate EBMs’ potential to improve healthcare and mitigate risk in pregnancy. We show that EBMs reach an AUROC and calibration similar to other popular methods such as XGBoost, logistic regression, and deep neural networks. Additionally, inspecting the shape functions learned by EBMs reveals surprising results that challenge traditional beliefs about the main contributors to pregnancy risks, and suggests more research should be done to accurately estimate fetal weights.

ACKNOWLEDGMENTS
We are deeply indebted to Professor Trevor Hastie for the intellectual discussions and his great feedback. We also thank the sites participating in OB COAP, the Foundation for Health Care Quality (FHCQ) and the OB COAP Management Committee for supporting this work. Additionally, FHCQ’s Ian Painter has helped tremendously in preparing the data.
(a) Displaying the individual risk contributions of the mother’s BMI and the mother’s age for preterm preeclampsia.

(b) Risk contribution of (i) the time from full cervical dilation to delivery, and (ii) the mother’s age to SMM.

Figure 2: Important shape functions for preterm preeclampsia (left) and SMM (right).

(a) Shoulder dystocia.

(b) SMM.

Figure 3: The risk contribution of race and ethnicity for shoulder dystocia and SMM. Preterm preeclampsia is similar. For SMM, the ‘Missing’ bucket represents 5.6% of the data for the feature ‘Race’, and 3.7% for ‘Hispanic or Latino ethnicity’. For shoulder dystocia, these are 4.8% and 4.0% respectively.

REFERENCES

[1] Michal Fishel Bartal, Avi Tsur, Baha M Sibai, Dvir Aran, Matthew J Bicocca, and Suneet P Chauhan. 2021. Clinical efficacy of a machine learning model for prediction of shoulder dystocia. American Journal of Obstetrics & Gynecology 224, 2 (2021), S409.

[2] Rachel Bennett, Zuber D Mulla, Pavan Parikh, Alisse Hauspurg, and Talayeh Razzaghi. 2022. An imbalance-aware deep neural network for early prediction of preeclampsia. Plos one 17, 4 (2022), e0266042.

[3] Leo Breiman. 2001. Random forests. Machine learning 45, 1 (2001), 5–32.

[4] William M Callaghan, Andrea P MacKay, and Cynthia J Berg. 2008. Identification of severe maternal morbidity during delivery hospitalizations, United States, 1991-2003. American journal of obstetrics and gynecology 199, 2 (2008), 133–e1.

[5] Carlo Cannarozzo. 2021. The merger-driven evolution of early-type galaxies and the connection with their dark matter halos. (2021).

[6] Abigail R Cartus, Ashley J Naimi, Katherine P Himes, Marian Jarlenski, Sara M Parisi, and Lisa M Bodnar. 2021. Can ensemble machine learning improve the accuracy of severe maternal morbidity screening in a perinatal database? Studies in health technology and informatics 264 (2019), 143.

[7] Cheng Gao, Sarah Osmundson, Xiaowei Yan, Digna Velez Edwards, Bradley A Malm, and You Chen. 2019. Learning to identify severe maternal morbidity from electronic health records. Studies in health technology and informatics 264 (2019), 143.

[8] Matt W Gardner and SR Dorling. 1998. Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmospheric environment 32, 14-15 (1998), 2627–2636.

[9] Eugene Declercq and Laurie Zephrin. 2020. Maternal mortality in the United States: a primer. Commonwealth Fund (2020).

[10] Tom Decroos and Jesse Davis. 2019. Interpretable prediction of goals in soccer. In Proceedings of the AAAI-20 Workshop on Artificial Intelligence in Team Sports.

[11] Foundation for Health Care Quality. 2022. Obstetrical Care Outcome Assessment Program (OCOAP). https://www.qualityhealth.org/obcoap/m

[12] Cheng Gao, Sarah Osmundson, Xiaowei Yan, Digna Velez Edwards, Bradley A Malm, and You Chen. 2019. Learning to identify severe maternal morbidity from electronic health records. Studies in health technology and informatics 264 (2019), 143.

[13] Trevor J Hastie and Robert J Tibshirani. 2017. Generalized additive models. Routledge.
[17] David G Kleinnbaum, K Dietz, M Gail, Mitchel Klein, and Mitchell Klein. 2002. Logistic regression. Springer.

[18] Kuinyu Joshua Lin, Gary E Rosenthal, Shawn N Murphy, Kenneth D Mandl, Yinzhu Jin, Robert J Glynn, and Sebastian Schneeweiss. 2020. External validation of an algorithm to identify patients with high data-completeness in electronic health records for comparative effectiveness research. Clinical Epidemiology 12 (2020), 133.

[19] Yin Lou, Rich Caruana, and Johannes Gehrke. 2012. Intelligible models for classification and regression. In Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, 150–158.

[20] Yin Lou, Rich Caruana, Johannes Gehrke, and Giles Hooker. 2013. Accurate intelligible models with pairwise interactions. In Proceedings of the 19th ACM SIGKDD international conference on Knowledge discovery and data mining, 623–631.

[21] Aaron E Maxwell, Maneesh Sharma, and Kurt A Donaldson. 2021. Explainable Boosting Machines for Slope Failure Spatial Predictive Modeling. Remote Sensing 13, 24 (2021), 4991.

[22] Mário WL Moreira, Joel JPC Rodrigues, Antonio MB Oliveira, Kashif Saleem, and Augusto J Venancio Neto. 2017. Predicting hypertensive disorders in high-risk pregnancy using the random forest approach. In 2017 IEEE International Conference on Communications (ICC). IEEE, 1–5.

[23] Harsha Nori, Samuel Jenkins, Paul Koch, and Rich Caruana. 2019. Interpretml: A unified framework for machine learning interpretability. arXiv preprint arXiv:1909.09223 (2019).

[24] Michelle JK Osterman, Brady E Hamilton, Joyce A Martin, Anne K Driscoll, and Claudia P Valenzuela. 2022. Births: final data for 2020. (2022).

[25] Jun Zhang Rafael T Mikolajczyk, Alexis DSilvestro. 2008. Evaluation of logistic regression reporting in current obstetrics and gynecology literature. PubMed 111 (2008).

[26] David A Squires. 2011. The US health system in perspective: a comparison of twelve industrialized nations. Issue Brief (Commonwealth Fund) 16 (2011), 1–14.

[27] A Tsur, L Batsry, S Toussia-Cohen, MG Rosenstein, O Barak, Y Brezinov, R Yoodl-Ullman, E Sivan, M Sirot, ML Druzin, et al. 2020. Development and validation of a machine-learning model for prediction of shoulder dystocia. Ultrasound in Obstetrics & Gynecology 56, 4 (2020), 588–596.

[28] Peter Xenopoulos, William Robert Freeman, and Claudio Silva. 2022. Analyzing the Differences between Professional and Amateur Esports through Win Probability. In Proceedings of the ACM Web Conference 2022. 3418–3427.

[29] Gen Yamada, Kayoko Hayakawa, Yuruka Asai, Nobuaki Matsunaga, Hiroshi Ohtsu, Masayuki Hojo, Masao Hashimoto, Kentaro Kobayashi, Ryo Sasaki, Tatsuya Okamoto, et al. 2021. External validation and update of prediction models for unfavorable outcomes in hospitalized patients with COVID-19 in Japan. Journal of Infection and Chemotherapy 27, 7 (2021), 1043–1050.

[30] Jiandong Zhou, Gary Tse, Sharen Lee, Tong Liu, William KK Wu, Zhudong Cao, Daniel Dajun Zeng, Ian Chi Kei Wong, Qingpeng Zhang, and Bernard Man Yung Cheung. 2020. Identifying main and interaction effects of risk factors to predict intensive care admission in patients hospitalized with COVID-19: a retrospective cohort study in Hong Kong. medRxiv (2020).