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Prediction of Childbirth Mortality Using Machine Learning

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Abstract. Timely identification of risk factors in the early stages of pregnancy, risk management and mitigation, prevention, adherence management can reduce the number of adverse perinatal outcomes and complications for both mother and a child. We have retrospectively analyzed electronic health records from the perinatal Center of the Almazov specialized medical center in Saint-Petersburg, Russia. Correlation analysis was performed using Pearson correlation coefficient to select the most relevant predictors. We used APGAR score as a metrics for the childbirth outcomes. Score of 5 and less was considered as a negative outcome. To analyze the influence of the unstructured anamnesis data on the prediction accuracy we have run two prediction experiments for every classification task: 1. Without unstructured data and 2. With unstructured data. This study presents implementation of predictive models for adverse childbirth events that provides higher precision than state of the art models. This is due to the use of unstructured medical data in addition to the structured dataset that allowed to reach 0.92 precision. Identification of main risk factors using the results of the features importance analysis can support clinicians in early identification of possible complications and planning and execution preventive measures.

Keywords. Childbirth, Machine learning, risk factors, prediction

Introduction

Timely identification of risk factors in the early stages of pregnancy, risk management and mitigation [1], prevention [2], adherence management [3,4] can reduce the number of adverse perinatal outcomes and complications for both mother and a child [5]. As the medical professionals already are overloaded, risk management can be partially assigned to the clinical decision support systems (CDSS) [6,7]. Such systems require a set of high-quality decision support models that are based on the validated medical data and are clinically interpretable [8]

The development of perinatal episodes is characterized by a significant number of heterogeneous interconnected factors with different contributions in etiological and pathological terms at different stages. This significantly complicates the development of decision support models. In this situation intellectual data analysis and data-driven models [9] can become an efficient basis for the clinical decision support. Thus, in [2] 47 patients with connective tissue dysplasia and 29 patients who did not have this syndrome were investigated on the basis of data from clinical and laboratory tests,

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ultrasound, Dopplerometry, Cardiotocography (CTG), Electrocardiogram (ECG) and echocardiography (ECHO-CG). In the effect of connective tissue dysplasia, was analyzed in 400 pregnant women using categorical variables responsible for the history, course and outcome of pregnancy. The final sample consisted of 350 features. The model allowed predicting the probability of complications in pregnancy and childbirth. The resulting forecast was accurate for 32 women out of 50, 16 women had more predicted complications, and 3 women had less predicted complications.

About 51% of the patients had complications; 86% had chronic fetal hypoxia, and 6% had premature detachment of the normally located placenta. These results are consistent with the results of the studies [10,11].

The study [12] focuses on identifying clinically significant predictors of neurocognitive development in newborns with perinatal human immunodeficiency virus (HIV). As a result of multifactor regression with gradient boost and 5-fold cross-validation, the predictors that have the greatest impact on the neurocognitive stability of a newborn were identified. In [13] it is shown that logistic regression models predict neonatal mortality with high accuracy. In [14] machine learning algorithms were compared with traditional methods in the task of early assessment of adverse risk in pregnant women.

In addition to analyzing individual studies, latest systematic reviews [15–20] have demonstrated the shortcomings of existing models and algorithms for supporting decision-making, especially in critical situations. The accuracy of classification and prognosis does not exceed 82%, which cannot be a satisfactory result. This is largely due to the lack of structured patient data, which makes it impossible to build sufficiently accurate mathematical models of pregnancy development.

Thus, despite the experience gained in developing decision-making models and forecasting of maternal risks, there is still room for improvement of the models. The development of such models will help to reduce complications and mortality during pregnancy and childbirth.

The goal of this study is to develop real world evidence data driven models based on semi-structured data for pregnancy risk prediction.

1. Methods

We have retrospectively analyzed electronic health records from the perinatal Center of the Almazov specialized medical center in Saint-Petersburg, Russia. The dataset was exported from the medical information system. It consisted of structured and semi structured data with the total of 73115 lines for 12989 female patients (Dataset A) for the period between 1st of January 2015 and 31st of December 2019**; and 103414 lines for 15681 newly born patients (Dataset B).** The data was extracted from two different HISes and later merged using mother identifier.

1.1. Data Preprocessing

1. We have extracted 73115 lines with 97 structured features with mother anamnesis (**Dataset A)**.

2. Mother ID (mother_id) was used as index to concatenate two data sets (mothers and newly born).

2.1 All the records from **Dataset B** that did not have a corresponding mother id from the Dataset A were removed.

2.2. All the lines from the Dataset A with no corresponding IDs from the Dataset B were removed.

2.3. All the lines that did not contain APGAR score were removed from the dataset as irrelevant for the study.

2.4. We removed all the lines without unstructured text anamneses

This resulted in a merged **Dataset C** with 2203 records for 2203 cases (mother + child)

We used APGAR score as a metrics for the childbirth outcomes. Score of 5 and less was considered as a negative outcome. A target column was added to the dataset: 1 if APGAR score > 5 and 0 if APGAR score <6

1.2. Correlation and Features Importance

Correlation analysis was performed using Pearson correlation coefficient to select the most relevant predictors.

1.3. Prediction Model

We ran an experiment for the classification of cases with APGAR score < 6. The data set was randomly divided into 70% training and 30% test sets. A random forest (RF) method was used for classification. RF fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting. To analyze the influence of the unstructured anamnesis data on the prediction accuracy we have run two prediction experiments for every classification task: 1. Without unstructured data and 2. With unstructured data.

1.4. Model Evaluation

Precision, Recall and F-measure were calculated as performance metrics for the experiments on the test data sets (30% randomly selected lines):

$$Precision = \frac{true\ positives}{true\ positives + false\ positives}$$

$$Recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

$$Fmeasure = 2 \cdot \frac{recall \cdot precision}{recall + precision}$$

2. Results

2.1. Correlation and Features Importance

Top most important features for the APGAR score < 6 are presented in Figure 1.

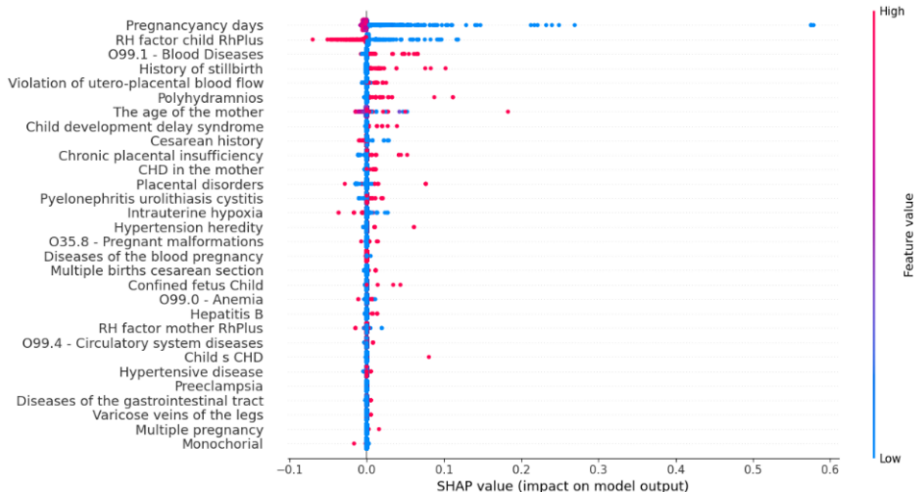

Figure 1. Features importance

As we can see, low APGAR score correlates with a stillbirth in anamnesis, aggravated obstetric history, mother's age, presence of scar on uterus, sexually transmitted infections,

A varicose of veins of the legs due to pregnancy, correlates with baby complications. Child development delay syndrome correlates positively with placental insufficiency and Fetal growth retardation syndrome. It also negatively correlates with emergency and spontaneous births. It is interesting to note that RH factor of a child more correlates to light asphalt more than to medium and even more than heavy asphyxia. The male gender of the child also has a slight correlation to the complications of the newborn. Table 1 presents the metrics for the APGAR score random forest prediction model. We can clearly see that considering unstructured data by the model significantly increases its forecasting precision (from 0.71 to 0.92)

Table 1. Prediction metrics with and without unstructured data

	Precision	Recall	F-measure
Only structured data	0.71	0.99	0.83
With unstructured data	0.92	0.99	0.88

3. Discussion and Conclusion

This study presents implementation of predictive models for adverse childbirth events that provides a higher precision than the state-of-the-art models. This is due to the use of unstructured medical data in addition to the structured dataset. Identification of main risk factors using the results of the features importance analysis can support clinicians in the early analysis of possible complications and planning and execution preventive measures.

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References

[1] English FA, Kenny LC, McCarthy FP. Risk factors and effective management of preeclampsia. Integr. Blood Press. Control. 2015 Mar 3; 8: 7-12. doi:10.2147/IBPC.S50641.
[2] Koullali B, Oudijk MA, Nijman TAJ, Mol BWJ, Pajkrt E. Risk assessment and management to prevent preterm birth. Semin. Fetal Neonatal Med. 2016 Apr; 21,2: 80-8. doi:10.1016/j.siny.2016.01.005.
[3] Kolkman DGE, Rijnders MEB, Wouters MGAJ, van den Akker-van Marle ME, van der Ploeg CPBK, de Groot CJM, Fleuren MAH. Implementation of a cost-effective strategy to prevent neonatal early-onset group B haemolytic streptococcus disease in the Netherlands. BMC Pregnancy Childbirth. 2013; 13: 155. doi:10.1186/1471-2393-13-155.
[4] Taranik M, Kopanitsa G. Using Machine Learning for Personalized Patient Adherence Level Determination. Stud. Health Technol. Inform. 2019; 261: 174-178.
[5] Hug L, Alexander M, You D, Alkema L. National, regional, and global levels and trends in neonatal mortality between 1990 and 2017, with scenario-based projections to 2030: a systematic analysis. Lancet Glob. Heal. 2019 Jun; 7,6: e710–e720. doi:10.1016/S2214-109X(19)30163-9.
[6] Kopanitsa G. A Qualitative Study of the Barriers and Opportunities for Adoption of Web-Portals for Doctors and Patients in Russia. J. Med. Syst. 2017; 41: 62. doi:10.1007/s10916-017-0713-8.
[7] Dudchenko A, Ganzinger M, Kopanitsa G. Optimization of Clinical Decision Support Based on Pearson Correlation of Attributes. Stud. Health Technol. Inform. 2019; 261: 199–204.
[8] Krikunov AV, Bolgova EV, Krotov E, Abuhay TM, Yakovlev AN, Kovalchuk SV. Complex data-driven predictive modeling in personalized clinical decision support for Acute Coronary Syndrome episodes. Procedia Comput. Sci. 2016; 80: 518-529. doi:10.1016/j.procs.2016.05.332.
[9] Tsui KL, Chen N, Zhou Q, Hai Y, Wang W. Prognostics and health management: A review on data driven approaches. Math. Probl. Eng. 2015; 6: 1-17. doi:10.1155/2015/793161.
[10] Tezikov YV, Lipatov IS, Frolova NA, Kutuzova OA, Prikhod'ko AV. Methodology of preventing major obstetrical syndromes. Vopr. Ginekol. Akušerstva i Perinatol. 2016; 15: 20–30. doi:10.20953/1726-1678-2016-2-20-30.
[11] Harrison CL, Lombard CB, East C, Boyle J, Teede HJ. Risk stratification in early pregnancy for women at increased risk of gestational diabetes. *Diabetes Res Clin Pract*. 2015; 107(1): 61-68. doi:10.1016/j.diabres.2014.09.006
[12] Paul R, Cho K, Mellins C, Malee K, Robbins R, et al. Predicting neurodevelopmental outcomes in children with perinatal HIV using a novel machine learning algorithm. BioRxiv. (2019) 632273. doi:10.1101/632273.
[13] Pollack MM, Koch MA, Bartel DA, Rapoport I, Dhanireddy R, El-Mohandes AAE, Harkavy K, Subramanian KNS. A Comparison of Neonatal Mortality Risk Prediction Models in Very Low Birth Weight Infants. Pediatrics. 2000; 105: 1051–1057. doi:10.1542/peds.105.5.1051.
[14] Pan I, Nolan LB, Brown RR, Khan R, van der Boor P, Harris DG, Ghani R. Machine Learning for Social Services: A Study of Prenatal Case Management in Illinois. Am. J. Public Health. 2017; 107: 938–944. doi:10.2105/AJPH.2017.303711.
[15] Aoyama K, D'Souza R, Pinto R, et al. Risk prediction models for maternal mortality: A systematic review and meta-analysis. PLoS One. 2018; 13(12): e0208563. doi:10.1371/journal.pone.0208563.
[16] Verstraete EH, Blot K, Mahieu L, Vogelaers D, Blot S. Prediction models for neonatal health care-associated sepsis: A meta-analysis. Pediatrics April 2015, 135,4: e1002-e1014. doi:10.1542/peds.2014-3226.
[17] Ukah UV, De Silva DA, Payne B, Magee LA, et al. Prediction of adverse maternal outcomes from pre-eclampsia and other hypertensive disorders of pregnancy: A systematic review. Pregnancy Hypertens. 2018 Jan; 11: 115-123. doi:10.1016/j.preghy.2017.11.006.
[18] Verhagen TEM, Hendriks DJ, Bancsi LFJMM, Mol BWJ, Broekmans FJM. The accuracy of multivariate models predicting ovarian reserve and pregnancy after in vitro fertilization: A meta-analysis. Hum Reprod Update. Mar-Apr 2008; 14,2: 95-100.doi:10.1093/humupd/dmn001.

[19] Lamain – de Ruiter M, Kwee A, Naaktgeboren CA, Franx A, Moons KGM, Koster MPH. Prediction models for the risk of gestational diabetes: a systematic review. Review Diagn Progn Res. 2017 Feb 8; 1: 3. doi:10.1186/s41512-016-0005-7.
[20] Sananès N, Langer B, Gaudineau A, Kutnahorsky R, et al. Prediction of spontaneous preterm delivery in singleton pregnancies: Where are we and where are we going? A review of literature. J Obstet Gynaecol. 2014 Aug; 34,6: 457-61. doi:10.3109/01443615.2014.896325.