Classification of the cardiotocogram data for predicting fetal health using machine learning techniques

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1. Introduction

The reduction of child mortality is the key interest of many countries and international organizations. According to UN's 2020 child mortality report, there has been outstanding improvement in child survival rate over the past three decades. However, there is still a long way to eradicate preventable deaths of newborns.

In line with fetal mortality, maternal mortality is also crucial, which accounts for 295,000 deaths during and following pregnancy and childbirth.[1] The vast majority of these deaths, 94 percent, occurred in low-resource settings, which mostly could have been prevented.

Cardiotocography (CTG) is the simple and economical way of evaluating fetal health and be used as an indicator for preventing child and maternal mortality. The basic logistics of CTG is to detect fetal heart rate and the activity of the uterine muscle with two transducers placed on the mother's abdomen, with one above the fetal heart to monitor heart rate, and the other at the fundus of the uterus to measure frequency of contractions. Doppler ultrasound provides the information, which is recorded on a paper strip, which is cardiotocograph(CTG). The purpose of this project is to predict fetal health and classify it from the range of 1 to 3 ("Normal", "Suspect" and "Pathological"). With the help of machine learning techniques, we will be able to interpret collected data with better accuracy. Also, in some countries where in lack of medical manpower, machine learning algorithms can contribute to providing relatively better and quicker predictions for mothers.

The academic goal of this project is to apply various machine learning models in the real dataset and figure out meaningful results from it. Also, rather than structured and refined dataset mainly for educational purposes, by facing various hiccups (i.e., missing values, outliers, high variance, etc.) from real dataset, we can develop techniques to cope with challenges.

1.1. Related Work

In work from 2015, Hakan and Abdulhamit analyzed cardiotocography data for predicting new-born critical health cases.[6] In this paper, the authors evaluate the classification performances of eight different machine-learning methods, including k-nearest neighbors and random forest, on the antepartum cardiotocography (CTG) data. We would like to take similar approaches to our data for data classification and prediction. Also, we would like to take some suggestions from this research.

2. Motivation

Recently there is a concern about declining birth rates in around the world. The main factor in low birth rate is economic prosperity, but there are some people who are reluctant to get pregnant because of fear of miscarriage or side effects during and after pregnancy, such as preeclampsia. In fact, the leading cause of death in infants under 5 years of age is death due to complications during labor in infants 1 month of age. According to CDC, almost 21,000 infants died in the United States in 2018.[2] The five leading causes of infant death in 2018 were: Birth defects, Preterm birth and low birth weight, Injuries (e.g., suffocation), sudden infant death syndrome and Maternal pregnancy complications. From these five causes, infant death by birth defect, Preterm birth, low birth and Maternal pregnancy complications can prevent using Cardiotocography. Cardiotocography method introduced in the 1970s with this method we can notice abortion rate have been decreased since 1980. It continues to decline, but the figure of 13.5 per 1,000 people recorded in 2017 is still high.

Cardiotocography is mainly used to check fetal well-being, before and during childbirth. And based on this record, the doctor can judge whether the pregnant woman is able to give birth, whether there are any side effects after childbirth, and the health of the fetus before and after childbirth. Fetal status is judged by the doctor by looking at the cardiotocography values. However, incorrect interpretation of cardiotocography can put the mother and the fetus at risk. For example, there are cases in which a cesarean section is required, but the diagnosis is made to have a natural childbirth. These controversies are still ongoing, and recent studies using machine learning are actively being conducted to reduce errors. For example, a wearable device

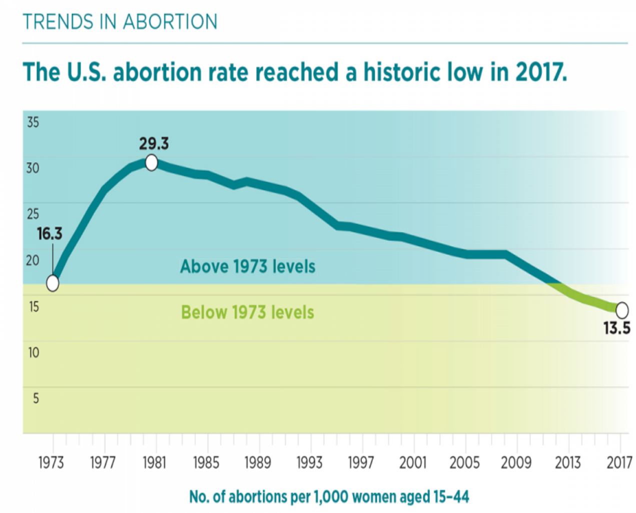

Figure 1. Number of abortions per 1,000 women aged 15-44 years, 1973-2017 from Guttmacher Institute [4]

capable of monitoring cardiotocography in real time has recently received FDA clearance.[5] It is also said that the wearable can provide the best results through real-time data collection. Cardiotocography research using such machine learning is an important study because it can reduce infant mortality and reduce maternal side effects and mortality.

Our main motivation is whether the interpretation of cardiotocography using machine learning is similar to the actual results. So, we used 2126 fetal cardiotocography data already classified into three categories ("Normal", "Suspect" and "Pathological") to create a model through an appropriate Transformer and Scikit-learn tool.

3. Evaluation

3.1. Method

For our project, using 22 features, we are going to compare various machine learning model to find best model of predict fetal state. The comparing model will be based on model we learn in class; K-Nearest Neighbor Method, Decision Trees and more. Moreover, we might reduce feature using PCA or other Dimensionality Reduction method to remove noise and improve performance. Since our data set have 22 features, there is chance to have noise in our data. We will divide data set into three subsets: train set, validation set and test set with the proportion of 60:20:20 using sci-kit module.

3.2. Metrics

Our goal is to make classification accuracy of our model as close to 100% and F1 Score to be close to 1. Accuracy, f1 score,precision and recall are the common method to evaluate multi class classification model. To prevent error from data imbalance, we will use all of four method.

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ number\ of\ predictions\ made}$$

$$F1\ Score = 2 \cdot \frac{Precision \cdot recall}{Precision + recall}$$

We may consider our project to be successful if at least one model get more than 85% in Accuracy and 0.8 in f1 score.

4. Resources

4.1. Data

We will use "Cardiotocography Data Set" provided by UCI Machine Learning Repository[3] Machine Learning Repository. Cardiotocography Data Set contain 2126 fetal cardiotocograms (CTGs) with 23 features. The CTGs were classified by three expert obstetricians and a consensus classification label assigned to each of them. The 23 features consist of the following data fields.

- LB - FHR baseline (beats per minute)
- AC – Number of accelerations per second
- FM - Number of fetal movements per second
- UC - Number of uterine contractions per second
- DL - Number of light decelerations per second
- DS - Number of severe decelerations per second
- DP - Number of prolongued decelerations per second
- ASTV - percentage of time with abnormal short term variability
- MSTV - mean value of short term variability
- ALTV - percentage of time with abnormal long term variability
- MLTV - mean value of long term variability
- Width - width of FHR histogram
- Min - minimum of FHR histogram
- Max - Maximum of FHR histogram
- Nmax - Number of histogram peaks
- Nzeros - Number of histogram zeros
- Mode - histogram mode
- Mean - histogram mean

- Median - histogram median
- Variance - histogram variance
- Tendency - histogram tendency
- CLASS - FHR pattern class code (1 to 10)
- NSP - fetal state class code (N=normal; S=suspect; P=pathologic)

4.2. Tool

Basically we will use Python and Jupyter notebook in our project. We will use tool based on what we learn in class like Numpy, Scikit-Learn, and some other package or API. However we might use R to visualization the data or plot.

5. Contributions

As a group, it is decided that all members of the group will participate across the entire pipeline of the project, from data cleaning to deriving and discussing results. For this proposal, Hyun worked on the introduction, resources and related work portion, Junghoon worked on the formatting of the proposal, evaluation and metrics and Kyle worked on the figures, motivation, and contribution parts of this proposal.

For the computational part of this project, Hyun will be responsible for data collection and exploratory analysis. Junghoon will be responsible for the implementation of methods and models. Lastly, Kyle will be responsible for model evaluation and the assessment of our overall experiments.

Under the evenly distributed tasks, every members of the group will help out where it is needed regardless of their tasks.

References

[1] Levels and trends in child mortality: 2020 report, population division.

[2] Causes of infant mortality:infant mortality. Centers for Disease Control and Prevention, 2021.

[3] D. Dua and C. Graff. UCI machine learning repository, 2017.

[4] R. K. Jones and E. Witwer. Induced abortion in the united states, May 2020.

[5] E. Reuter. Startup gets fda clearance for device that can monitor baby's heart rate, Mar 2020.

[6] H. Sahin and A. Subasi. Classification of the cardiotocogram data for anticipation of fetal risks using machine learning techniques, 2015.