Machine Learning Engineer Nanodegree
Capstone Proposal

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Domain Background

Delivering babies is not only stressful for the family, but also intense for the supporting doctors and nurses. Different than most other treatments and operations, parturition can take place at any time, which makes OBGYN a 24-7 department in most places. Generally, doctors look at the fetus heart rate plot to determine the health status of the fetus, namely putting them into three categories (1 to 3); 1 being the healthy status, 3 being the unhealthy status that needs immediate attention and/or a C-section, 2 being the grey area that requires more attention. The unattended category 3 fetus can suffer brain damage or even death in a matter of few minutes. The widen usage of Pitocin, which intensify uterus contraction, further expedite the damage. With the mix of different level of experience, fatigue due to long hours and intense work load, and short of staff at late hours, misclassification of fetus status and slow response to category 3 patients have been causing numerous incidents in an ongoing manner. This not only result in broken heart families, but also cost billions of dollars in lawsuit to the industry. Similar studies have been done, such as *A Machine Learning Approach to the Detection of Fetal Hypoxia during Labor and Delivery* [1]; however, it achieved only 50% recall with false positive rate at 7.5%. With the rise in machine-learning technologies, especially deep neural network, I see the opportunity to create a product that dynamically classifies fetus health status that acts as a second eye for doctors, in the goal of prevent tragedies.

Prior to this opportunity, I had collaborated with LBGYN doctors from St. Luke hospital in Allentown, PA, to resolve this very same issue as part of my college project. However, due to the lack of knowledge in machine learning, I simplified the warning system to use a hard threshold that based on fetus heart rate. With this capstone project and the discovery of public fetus health dataset, I see the opportunity to create a much better model that help predict fetus health status based on various metrics.

Problem Statement

The inaccuracy and human errors in determining fetus health status at delivery time have been causing numerous tragedies from time to time. This problem is more severe during night time when doctors and nurses are tired and the department is low on staff. Although computer aid fetus health warning systems have been in place for a long time, most of such systems use simple threshold on heartrate to send out warnings, which is imaginably inaccurate. in Due to advancement in machine learning technologies, the creation of a more accurate computer aid fetus health classification tool and warning system is increasingly realistic.

Ideally the input to the machine learning model will capture the fetus status at the very moment, such as heartrate for the minute, number of uterine contractions, fetal movement; it should also include data that the fetus health trend, such as heartrate acceleration/deceleration. The target output will be category 1 to 3, which indicates normal, suspect, and pathologic. As the output indicates, this will be a multi-class (3 classes) classification problem.

Dataset and Inputs

I will use Cardiotocography dataset [2], from UCI machine learning repository, as the solo dataset for this project. This dataset is directly related to the purposed problem: it contains 2126 instances, each with 21 input attributes and the NSP output attributes (3 category class codes). As the inputs are readily available attributes from most fetus heartrate monitors, a model created based on this dataset can potentially be a plug-in for existing heartrate monitoring systems.

Out of the 2126 data points, 1657 having category 1, 297 having category 2, and 178 having category 3. Like most disease related dataset, this dataset is skewed towards the healthy category. As a result, a f1-score that give more weight to recall will be a much better evolution metric comparing to accuracy.

Solution Statement

The resulting product will be a classification model created based on the prior described dataset. In creating this model, I will try various classification algorithms including neural network, to achieve better performance. In addition to the model, an API will be created using AWS Lambda, making the model readily accessible by other systems.

Benchmark Model

Based on radiopaedia.org, a health fetus will have heartrate between 120 and 160 bpm. I will use a hard threshold, 120 – 160 bpm, to simulate a traditional fetus health predictor, and use it as the benchmark model. This benchmark model will simply predict a category 1 when heart rate is between 120 – 160 bpm, and category 3 when heart rate is out of this range. A F1 score will be calculated against this simple model for comparison and performance evaluation.

Evaluation Metrics

As the dataset is skewed towards fetus with category 1, accuracy will not be a good evaluation metrics. Instead, F1-score is a great option since it puts weight on both the false positive and false negative. In addition, false negative (fetus belong to category 3 is not classified as category 3) is a much severe problem than false positive; therefore, a F1-score with more weight on recall, larger beta, will help reduce the number of false negatives.

Project Design

The workflow of the solution includes: data cleaning (eliminate highly correlated columns, transform and scale data to between 0 and 1, remove outliers if any, etc), split data to training set and testing set, try multiple models (neural network, regression, Gaussian naïve bayes, random forest, etc) and compare performance, pick best model for fine tuning, output model, and finally create API to productionize created model.

References

[1] *A Machine Learning Approach to the Detection of Fetal Hypoxia during Labor and Delivery*, by Philip A. Warrick, Emily F. Hamilton, Robert E. Kearney and Doina Precup
https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=1&cad=rja&uact=8&ved=0ahUKEwjL47v2gYjYAhVr2oMKHdGOBAQQFggsMAA&url=https%3A%2F%2Fwww.aaai.org%2Focs%2Findex.php%2FIAAI%2FIAAI10%2Fpaper%2Fdownload%2F1597%2F2372&usg=AOvVaw07ZNZJvDTi6NyI8BUqenlm

[2] https://archive.ics.uci.edu/ml/datasets/Cardiotocography#