

Perinatal Hypoxia Diagnostic System by using Scalable Machine Learning Algorithms

Harmandeep Kaur, Vikas Khullar, Harjit Pal Singh, Manju Bala

Abstract: Collaborating big data and machine learning approaches in healthcare can help in improving clinical decision making and treatment by identifying and accumulating accurate features. Prenatal hypoxia can also be identified by cardiotocography (CTG) monitoring that helps in identifying the condition of the fetus. Imposing the data over distributed approaches can help in fast computation to rate the fetal and mother wellbeing before delivery. Our research aims to propose and implement a scalable Machine learning Algorithm based perinatal Hypoxia diagnostic system for larger datasets. This system was implemented on the CTG dataset using python and pyspark models like SVM, Random Forest, and Logistic regression. In the proposed method experiment results contributing to spark RF are more accurate than other techniques and achieved the precision of 0.97, recall of 0.99, f-1 score of 0.98, AUC of 0.97 and gained 97% accuracy.

Keywords- Prenatal hypoxia, CTG, pyspark, fetal state, and machine learning techniques.

I. INTRODUCTION

Perinatal Hypoxia is a disease in neonates caused by an inadequate supply of oxygen. Since the brain of the neonate is very delicate, it can easily influence by the supply of oxygen, the discomfort caused by lack of oxygen may lead to inconceivable cases [1][2]. The spectrum ranges from non-life-threatening to life-threatening during pregnancy and delivery. Hypoxia identification during labor becomes the goal to diminish the chance of permanent damage [3]. Thus, a scalable and effective system is required to analyze perinatal hypoxia that should be real-time and robust, and assists gynaecologist to take an appropriate decision promptly for future complications [1][2][20]. Efforts have been made to develop a computer system for analyzing the fetal state from features in CTG record.

Intrapartum continuous monitoring of neonate becomes most important so that obstetricians can monitor the fetal heart rate concerning uterine contractions which in return will help in controlling the morbidity and mortality both in mother and newborn [3][20]. Figure 1 shows typical CTG recordings

(FHR signals [4] and UC signals [6]). Simultaneous recording of mother's uterine contraction and fetal heart rate (FHR) is known as cardiotocography (CTG), the machine traces the recordings on a paper is called Cardiotocograph, most commonly known as electronic fetal monitoring (EFM). CTG can be internal and external. Internal CTG uses a scalp electrode, attached directly to the baby's head through cervical opening or by a ruptured amniotic sac. External CTG uses two transducers; Doppler's ultrasound transducer; that monitors the fetus heart rate and pressure transducer; monitors contractions, placed on the mother's abdomen, this can also be in the form of belt to restrict motility. [5]

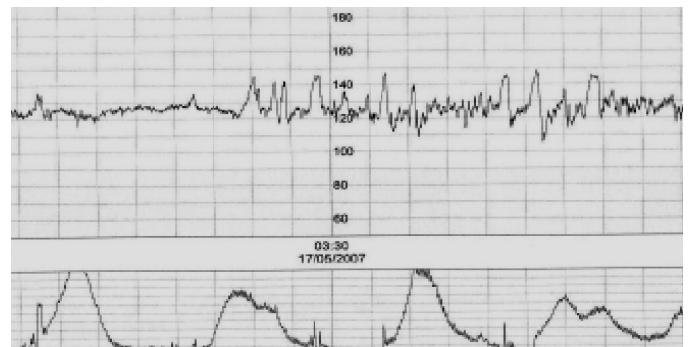


Figure 1: CTG and UC signals [4][6]

CTG data analysis through Machine learning approaches helps in early-stage preventions, saving lives of mother and fetus, neonate's severe or minor damage and save diagnostic time for obstetricians as CTG data holds antenatal information like UC and fetus movements inside mother's abdomen so that obstetricians or gynecologists can make use of this information[16]. Cesarelli et al. (2009) in his research does the classification of fetal hypoxia based on the patient's past and present medical history through CTG data analysis and also stated that feature extraction is challenging task to separate it from other common fetal risks during pregnancy [11].

Heart of the baby begins to form and beat within the first trimester of pregnancy and as per Grivell et al. (2012) CTG monitoring is applicable for fetus only after 7 months of pregnancy [15]. Gribbin and Thornton (2006) says that normal or accepted baseline fetal heart rate ranges from 110-160 beats per minute (bpm) and variance between 5 and 25. Factors such as an increase in variability of more than 25 bpm known as marked variability, and tachycardia can be associated with fetal hypoxia. [12][13]. According to Ma and Zhang (2015) maternal smoking, anemia, birth asphyxia, inadequate fetal monitoring, deficit placenta, and high altitude pregnancy can be other sources of fetal hypoxia [14]. Big data in healthcare may have taken a slower start but today we

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have many sophisticated sensors connected to the body and present in wearable like clothes, watches etc. that provides continuous monitoring of heart, blood pressure, exercises, steps counting and many more. Machine learning is a technique that learns for themselves so combining these technologies provides a vibrant system that has gain the potential success and is easy to access.[18][21]

II. METHODOLOGY AND MODELS

A. Description of data

Data used is taken from the UCI Machine Learning Repository, which was derived from a study at the University of Porto. 2126 fetal records were automatically processed and classification was based on morphological patterns as well as on a fetal state [22][23]. By SisPorto2.0, 21 diagnostic features were measured [7] and in the proposed approach out of 1950 sample, 1655 were classified as normal and 295 as suspect fetal state. 21 features are illustrated in table 1. We implemented various machine learning algorithms on big data platform to analyze perinatal hypoxia (Figure 3).

Table 1 shows a description of 21 input features

Sr. no.	Features	Description
1	LB	FHR baseline (beats per minute)
2	AC	Acceleration per second
3	FM	Fetal movement per second
4	UC	Uterine contractions per second
5	DL	Light decelerations per second
6	DS	Severe decelerations per second
7	DP	Prolonged decelerations per second
8	ASTV	Percentage of time with abnormal short term variability
9	MSTV	Mean value of short term variability
10	ALTV	Percentage of time with abnormal long term variability
11	MLTV	Mean value of long term variability
12	Width	Width of FHR histogram
13	Min	Minimum of FHR histogram
14	Max	Maximum of FHR histogram
15	Nmax	# of histogram peaks
16	Nzero	# of histogram zeros
17	Mode	Histogram mode
18	Mean	Histogram mean
19	Median	Histogram median
20	Variance	Histogram variance
21	Tendency	Histogram tendency

B. Algorithms

Machine learning (ML) is an application of Artificial Intelligence (AI) that makes the computer systems to learn themselves on the basis of patterns and assumptions by using the study of algorithms and statistical models. Machine learning can be supervised, unsupervised and reinforcement type. In traditional programming data and algorithm decides the output whereas in Machine Learning output defines the algorithm to be implemented on the given data. [8][10][19]

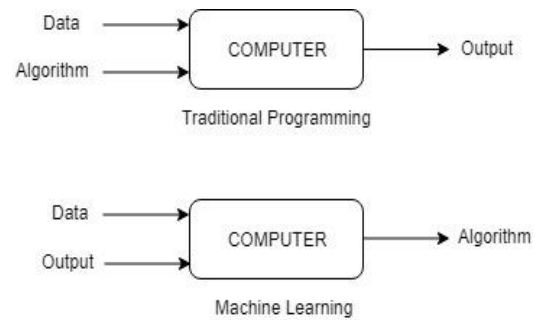


Figure 2: Outline of Machine Learning [8]

1. Linear Regression

Linear regression model is a supervised learning technique used to find out the linear relationship between the dependent variable and series of changing independent variables and hence, the name is Linear Regression [19]. The main objective is to predict the Best Fit Line (straight line passes through the centroid of data points), so that the vertical distance between each of the independent variable point from the line should be minimal [8].

Hypothesis Function for linear regression:

$$Y = B_0 + B_1 * X \quad (1)$$

Where,

Y = prediction/output / dependent variable

B₀ = intercept

B₁ = slope or coefficient of x

X = input / independent variable

2. Logistic Regression

This supervised learning algorithm is used for classification problems and predicts the probability between 0 and 1 of the target class. This becomes possible by using a nonlinear function (also called logistic function or sigmoid function) that converts the form of output from continuous to probability [19]. In this model, the output or target values can take only distinct values for given input values (or features) and builds the regression model to predict probability [9].

Logistic regression models the data by sigmoid function:

$$g(z) = 1/(1 + e^{-z}) \quad (2)$$

By (1):

$$g(z) = 1/(1 + e^{-(B_0 + B_1 * X)}) \quad (3)$$

The output curve formed is called Logistic Curve and usually an S-shaped.

3. Support Vector Machine(SVM)

SVM is a supervised learning technique used for classification and regression problems. It discriminates the data by a hyperplane that fairly separates two classes.

Along with the linear classification, SVM can also perform non-linear classification by mapping the input to n-dimensional space where coordinates represent the value of n (number of features) [10][24].

4. Random Forest(RF)

This algorithm can also be used for classification and regression problems. Decision trees are the fundamental building blocks of random forest algorithm. Random forest classifier algorithm uses multiple decision trees that work independently. An individual tree makes a class prediction and class with the majority is the ultimate prediction. [11][18]

5. K-fold Cross-Validation

Cross-validation is a statistical technique used to estimate the accuracy of a predictive model; the one where the goal is a prediction. Usually, data in a prediction problem is divided into training data, that is used to fit the model and testing or validation data, used to determine the performance of the model. Cross-validation is used to evaluate machine learning models over limited dataset.

In k-fold cross-validation, data is divided into k equal parts and relevant iterations are performed over one part as testing set and other k-1 as training set. Lastly, performance metrics are analyzed to determine accuracy, roc, sensitivity and other useful metric. [17][25]

6. Software Tools

There are various tools and systems available to predict the fetal state. Here, we used the open-source cluster-computing "PySpark Programming" framework for this paper. PySpark is the combination of Apache Spark and Python. It is a world-wide popular software that is easy to use, fast, general-purpose and also uses high-level programming language (Python). PySpark is majorly used for machine learning and real-time streaming analytics and also provides a variety of built-in libraries. Python provides simplicity whereas Apache Spark has the power to tame Big Data.

C. Procedure

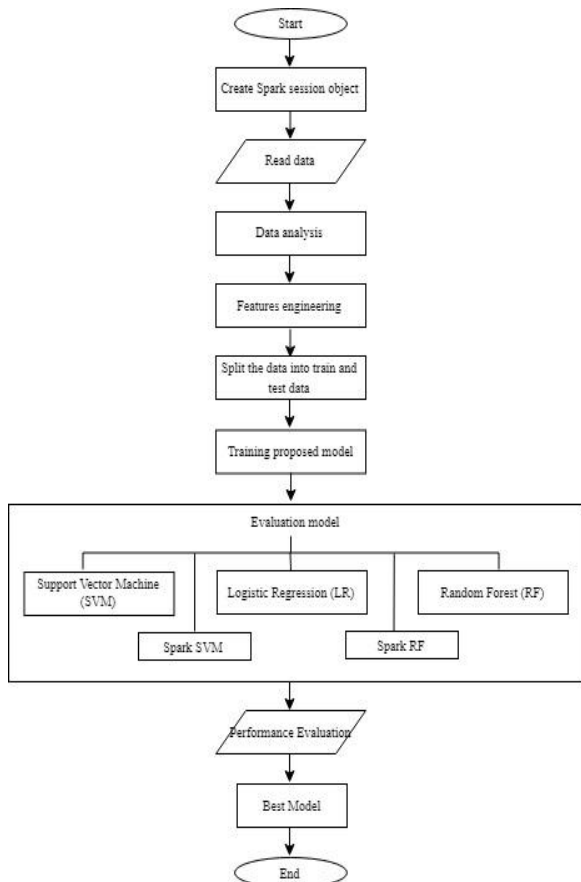


Figure 3 Implementation procedure

a) **Create a spark session object:** session is a temporary interaction between two or more communicating devices or entities. Spark session is an entry point to provide a way

- of interaction with various spark functionality and make it easy to program with Data frames and Dataset.
- b) **Read data:** dataset is then read and load within the spark using data frames. Dataset need to be placed within the same directory or correct path of location need to be mentioned.
- c) **Data analysis:** This is the process of evaluating the data to discover useful information. This deeper inspection of the dataset is drilled, starting with validating the shape and to end by finding the correlation between input and output variables.
- d) **Feature engineering:** in this part, we combined all the input features to a single vector by using VectorAssembler. It created a single feature that captures all the inputs of a row. Instead of multiple input columns, it merges all the input columns to a single vector column.
- e) **Split the data into train and test data:** data is then split into training and testing data to train and evaluate the performance of the applied algorithm respectively. We split the data into 4 ratios 60/40, 70/30, 80/20 and 90/10 in which the first part shows the ratio of training data and rest is testing data.
- f) **Training models:** here, we build and train various models using 21 input features described in data along with the output feature named features and labels respectively.
- g) **Evaluating models:** the final part of any exercise is to check the performance. In this part, performance is evaluated by checking accuracy, execution time, mean squared error, area under ROC curve and various other parameters.

D. Performance Evaluation

Evaluation of a model can be measured by various parameters but accuracy is the most obvious one. To completely understand the performance, a confusion matrix is generated that contains actual and predicted values. [26]

Table 2 Confusion Matrix

Actual/Prediction	Predicted (true)	Predicted (false)
Actual (true)	True Positive	False Negative
Actual (false)	False Positive	True Negative

Various other criteria for evaluating the parameters are mentioned below:

1. **Accuracy:** score shows how correct or precise a model is.
Accuracy = (TP+TN) / (TP+TN+FP+FN)
2. **F-1 Score:** harmonic mean between precision and recall. F1 is the best value at 1 and worst at 0.
F1score=2 * ((precision*recall) / (precision+recall))
3. **Precision:** is the fact of being accurate that is when the model predicted true and how often it is correct.
Precision = TP / (TP+FP)
4. **Recall:** when the results are actually true and how often it predicts true.
Recall = TP / (TP+FN)
5. **Area Under Curve (AUC):** is an abbreviation for Area Under Curve, is the analysis of model, capable to distinguish classes well. Higher the AUC, higher the correct prediction.

6. Execution Time: how much time the system spent executing the model or the task.

III. EXPERIMENTAL RESULTS

The accuracy score for SVM was 91% based on restricted data set with 1950 records and 2 output classes to predict fetal state. Using a simple machine learning algorithm on a big data platform performs better. The accuracy for spark SVM came as 91% similarly for random forest 96% of accuracy was measures whereas spark SVM and RF gave 93 and 97% respectively, as the total accuracy. Other parameters of the metrics such as f1 score, precision, recall, AUC also gave slightly different results when compared with spark algorithms. Results are mentioned in table 3.

Table 2 Results for proposed methods

	Accuracy (in %)	Precision	Recall	F-1 Score	AUC
SVM	91	0.91	0.97	0.95	0.71
RF	96	0.96	0.96	0.97	0.97
SPARK LR	93	0.96	0.97	0.96	0.97
SPARK SVM	93	0.96	0.97	0.96	0.96
SPARK RF	97	0.97	0.99	0.98	0.97

Each bar graph predicts the difference among various parameters and compares with one another. Accuracy chart shows the highest accuracy of Spark RF among others as 97%, Spark LR and Spark SVM gave same accuracy measure as 93% whereas 91 and 96% is gained by SVM and Random Forest respectively. F-1 score for every proposed model seems to have approximately equal measure. Precision for Spark RF shows difference of 0.01 units among other models. Bar of Recall for Spark RF counted as 0.99 whereas, other algorithm has approximately equal count. AUC for each model seems to have nearly same calculations except SVM (0.71).

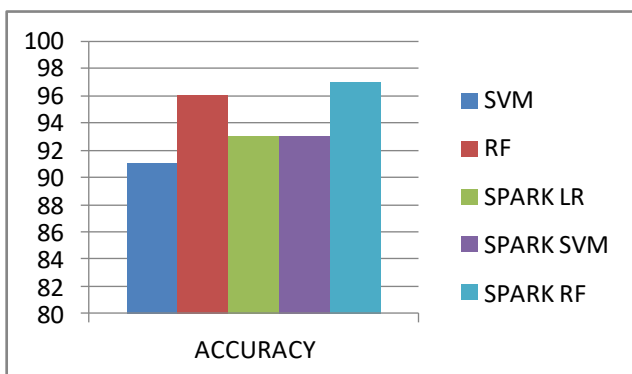


Figure 4 Comparison of Accuracy

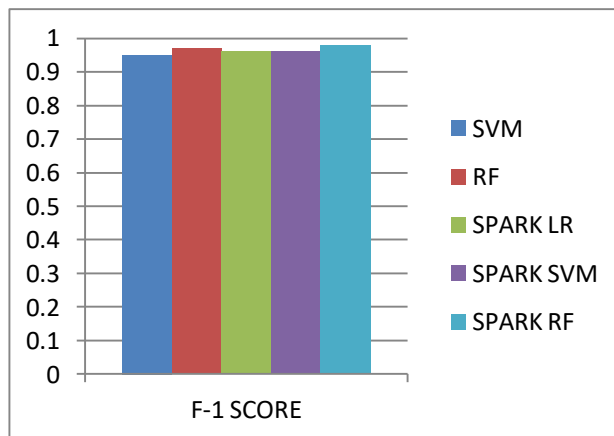


Figure 5 Comparing F-1 Score

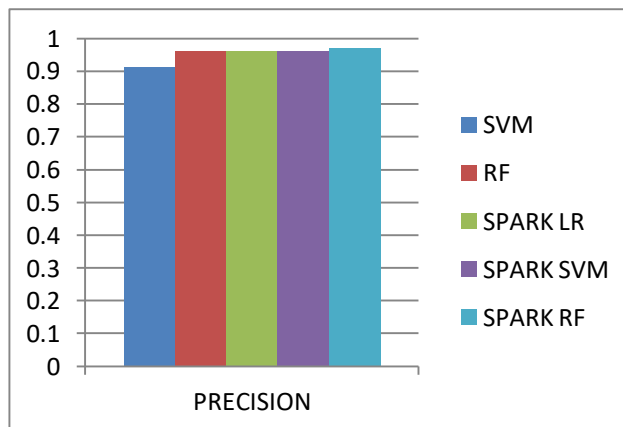


Figure 6 Comparison of Precision

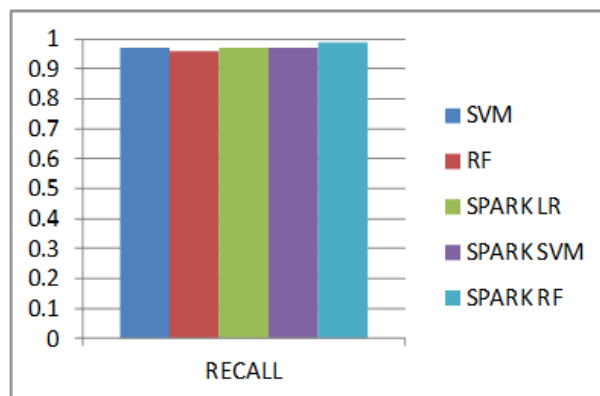


Figure 7 Comparing Recall

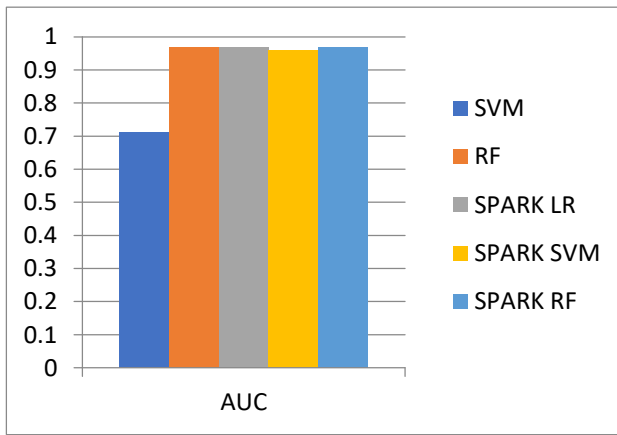


Figure 8 Comparison of Area under Curve

IV. CONCLUSION

The right inference of CTG records can help in the early-stage prediction of fetal condition. This study aimed to imitate a solution using big data with various machine learning algorithms like SVM, RF. Simple SVM and RF are compared with Sparks' which makes machine learning algorithm to be easily scalable. Using the K-fold technique, the accuracy index was determined; the proposed, Spark RF, shows higher accuracy (97%) among other studies. Not only accuracy, precision (0.97), recall (0.99), AUC (0.98) also shows a slight difference. Hence, our system is capable to work effectively over a scalable dataset.

In the future, more big data computations, other machine learning algorithms such as unsupervised and reinforced algorithms can be enacted. Also, work can be shifted over deep learning models.

REFERENCES

- Oscar Barquero-Pérez et al., "Fetal heart rate analysis for automatic detection of perinatal hypoxia using normalized compression distance and machine learning," *Front. Physiol.*, vol. 8, no. FEB, 2017.W.-K. Chen, *Linear Networks and Systems* (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.
- M. S. Iraj, "Prediction of fetal state from the cardiogram recordings using neural network models," *Artif. Intell. Med.*, vol. 96, pp. 33–44, 2019.B. Smith, "An approach to graphs of linear forms (Unpublished work style)," unpublished.
- M. J. Stout and A. G. Cahill, "Electronic Fetal Monitoring: Past, Present, and Future," *Clin. Perinatol.*, vol. 38, no. 1, pp. 127–142, 2011.
- M. G. Signorini, G. Magenes, S. Cerutti, and D. Arduini, "Linear and nonlinear parameters for the analysis of fetal heart rate signal from cardiogram recordings," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 3, pp. 365–374, 2003.
- Z. Alfirevic, D. Devane, G. M. L. Gyte, and A. Cuthbert, "Continuous cardiogram (CTG) as a form of electronic fetal monitoring (EFM) for fetal assessment during labor," *Cochrane Database Syst. Rev.*, vol. 2017, no. 2, 2017.
- M. Romano, P. Bifulco, M. Cesarelli, M. Sansone, and M. Bracale, "Foetal heart rate power spectrum response to uterine contraction," *Med. Biol. Eng. Comput.*, vol. 44, no. 3, pp. 188–201, 2006.
- A. Garrido, D. Ayres-de-Campos, and J. Marques-de-Sa, "Cardiograms," vol. 318, no. November 1999, pp. 311–318, 2000.
- N. B. Muppalaneni, M. Ma, and S. Gurumoorthy, *Soft Computing, and Medical Bioinformatics*. Springer Singapore, 2019.
- The Pennsylvania State University, "STAT 504 | Analysis of Discrete Data". <https://onlinecourses.science.psu.edu/stat504/node/149>
- R. Gholami and N. Fakhari, *SUPPORT VECTOR MACHINE* :, 1st ed. Elsevier Inc., 2017.
- M. Cesarelli, M. Romano, and P. Bifulco, "Comparison of short term variability indexes in cardiogram fetal monitoring," vol. 39, pp. 106–118, 2009.

- D. Analytics, "Application of Machine Learning Techniques to classify Fetal Hypoxia Krishna Mohan Mishra Supervisor :"
- D. Analytics, "Application of Machine Learning Techniques to classify Fetal Hypoxia Krishna Mohan Mishra Supervisor :"
- Q. Ma and L. Zhang, "Progress in Neurobiology Epigenetic programming of hypoxic-ischemic encephalopathy in response to fetal hypoxia," *Prog. Neurobiol.*, vol. 124, pp. 28–48, 2015.
- G. Rm, Z. Alfirevic, G. Gml, and D. Devane, "Antenatal cardiogram for fetal assessment (Review)," no. 9, 2015.
- D. Ayres-de-Campos, C. Costa-Santos, M. Validation, and S. Group, "Prediction of neonatal state by computer analysis of fetal heart rate tracings : the antepartum arm of the SisPorto 1 multicentre validation study," vol. 118, pp. 52–60, 2005.
- R. Kohavi, "A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection," no. March 2001, 2013.
- M. Iii, "Big data and machine learning in critical care : Opportunities for collaborative research Organizing Committee of the Madrid 2017 Critical Care Datathon," vol. 43, no. 1, pp. 52–57, 2019.
- R. Bandi and G. Anitha, "Machine learning based Oozie Workflow for Hive Query Schedule mechanism," 2018 Int. Conf. Smart Syst. Inven. Technol., no. Icssit, pp. 513–517, 2019.
- P. A. Warrick, E. F. Hamilton, R. E. Kearney, and D. Precup, "A machine-learning approach to the detection of fetal hypoxia during labor and delivery," *AI Mag.*, vol. 33, no. 2, pp. 79–90, 2012.
- A. L. Beam and I. S. Kohane, "Big data and machine learning in health care," *JAMA - J. Am. Med. Assoc.*, vol. 319, no. 13, pp. 1317–1318, 2018.
- M. G. Signorini, A. De Angelis, G. Magenes, R. Sassi, D. Arduini, and S. Cerutti, "Classification of fetal pathologies through fuzzy inference systems based on a multiparametric analysis of fetal heart rate," *Comput. Cardiol.*, pp. 435–438, 2000.
- Frank, A. and A. Asuncion, *UCI Machine Learning Repository* [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California. School of information and computer science, 201.213 .0
- Georgoulas, G., D. Stylios, and P. Groumpos, Predicting the risk of metabolic acidosis for newborns based on fetal heart rate signal classification using support vector machines. *IEEE Transactions on biomedical engineering*, 2006. 53(5): p. 875-884
- T. Fushiki, "Estimation of prediction error by using K-fold cross-validation," *Stat. Comput.*, vol. 21, no. 2, pp. 137–146, 2011.
- L. C. Briand, J. Wüst, J. W. Daly, and D. Victor Porter, "Exploring the relationships between design measures and software quality in object-oriented systems," *J. Syst. Softw.*, vol. 51, no. 3, pp. 245–273, 2000.

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