Fetal Birth Weight Estimation in High-risk Pregnancies through Machine Learning Techniques

Mário W. L. Moreira[1,2], Joel J. P. C. Rodrigues[1,3], Vasco Furtado[4],
Constandinos X. Mavromoustakis[5], Neeraj Kumar[6], Isaac Woungang[7]

[1] Instituto de Telecomunicações, Universidade da Beira Interior, Covilhã, Portugal
[2] Instituto Federal de Educação, Ciência e Tecnologia do Ceará (IFCE), Aracati, CE, Brazil
[3] National Institute of Telecommunications (Inatel), Santa Rita do Sapucaí, MG, Brazil
[4] University of Fortaleza (UNIFOR), Fortaleza, CE, Brazil
[5] University of Nicosia, Nicosia, Cyprus
[6] Computer Science & Engineering Department, Thapar University, Patiala (Punjab), India
[7] Department of Computer Science, Ryerson University, Ontario, Toronto, Canada

{mario.moreira, joeljr}@ieee.org; vasco@unifor.br; mavromoustakis.c@unic.ac.cy;
neeraj.kumar@thapar.edu; iwoungan@scs.ryerson.ca

***Abstract*— The low weight of fetus at birth is considered one of the most critical problems in pregnancy care, affecting the newborn's health and leading it to death in more severe cases. This condition is responsible for the high infant mortality rates worldwide. In health, artificial intelligence techniques, especially those based on machine learning (ML), can early predict problems related to the fetus' health state during entire gestation, including at birth. Hence, this paper proposes an analysis of several ML techniques capable of predicting whether the fetus will born small for its gestational age. The results show that the hybrid model, named bagged tree, achieved excellent results concerning accuracy and area under the receiver operating characteristic curve, to know, 0.849 and 0.636, respectively. The importance of the early diagnosis of problems related to fetal development relies on the possibility of an increase in the gestation days through timely intervention. Such intervention would allow an improvement in fetal weight at birth, associated with a decrease in neonatal morbidity and mortality.**

***Index Terms*—Electronic health systems; Artificial intelligence; Machine learning; Medical conditions; Pregnancy**

I. Introduction

Nowadays, the quantity of newborns with low birth weight has increased. Intrauterine growth restriction (IUGR) is a disorder in which the fetus is smaller in stature compared with others with the same gestational age. This condition limits the growth of the baby's body and organs [1]. Neonates with IUGR can have problems at birth, such as low oxygen level, low Apgar score, respiratory difficulties due to meconium aspiration or hypoglycemia. Severe cases can cause fetal death or long-term growth problems. Maternal hypertension is the primary cause of IUGR, although there are still significant difficulties in determining the different types of hypertension during the pregnancy-puerperal cycle. In this sense, persistent arterial hypertension is, independently of its etiology, responsible for the most severe fetal growth disorders [2].

The health services area is one of the most benefited by the diffusion of machine learning (ML) approaches. ML belongs to a subfield of artificial intelligence (AI) that uses data collected on a large scale to recognize patterns and trends that would be undetectable by human observers [3]. In this way, it allows a system to incorporate new information and learn from experience, automatically correcting parameters and increasing the ability to recognize patterns and predictions of behavior. The larger the databases, the more powerful is the learning ability of those systems. This paradigm allows AI systems to learn, *e.g.*, thousands of diagnoses and medical guidelines on the most diverse diseases [4]. In examining their patients, clinicians can insert case characteristics into the system and generate the most probable diagnostic assumptions [5]. In this sense, ML algorithms allow reducing the number of possible diagnoses in more complex cases, producing more precise indications of exams and treatments. Therefore, ML-based algorithms represent a powerful tool to assist the health professional in the decision-making process.

Regarding the Big Data paradigms, it is possible, through innovative ML techniques, to analyze a significant amount of data from pregnant women and to provide obstetricians/gynecologists with more detailed information on fetal health during and after pregnancy [6]. The early identification of increased risk of complications due to low birth weight can provide guidance and treatment adapted to risk profiles and individual needs. Besides, the health area also tends to adhere firmly to the Internet of Things (IoT) paradigms for monitoring patients through various devices that can transmit data about the clinical condition of the patient that needs constant monitoring [7]. There is also the ease of data storage and remote access through cloud computing [8]. Therefore, constant monitoring of fetal health through information and communication technologies can reduce mortality and morbidity rates, contributing to a better quality of life for both mother and baby. Hence, the main contributions of this paper are as follows:

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- A comprehensive review of architectures and concepts capable to support the health expert in high-risk pregnancy monitoring.
- A study of algorithms based on ML techniques and their use in the prediction of risk situations related to fetal care.
- A performance assessment study of different techniques using a cross-validation method and its related indicators.

The remainder of the paper is organized as follows. Section II elaborates on related work about the topic focusing on ML methods and their application in healthcare. Section III describes the adaptation of these ML-based approaches to predict fetal birth weight. The performance evaluation, comparison of various methods, and the results analysis of the proposed techniques are presented in Section IV. Finally, Section V concludes the study and suggests further works.

II. Related Work

This topic discusses the use of ML techniques in health, as well as architectures for data acquisition, processing, and storage. Also, it presents a study related to the newborn small for gestational age (SGA) care.

A. Decision Tree-based Predictive Classifiers for Risk Pregnancy Care

In [9], Moreira *et al.* proposed an inference mechanism for smart decision support systems through performance comparison of various ML techniques. The main contribution of this study was to identify hypertensive disorders related-problems that can worsen the pregnant woman's clinical condition. The use of hybrid decision tree-based techniques was also presented. The results showed a good performance concerning the confusion matrix indicators for the prediction of high-risk situations for the pregnant woman, contributing to the reduction of mortality and morbidity rates for both mother and baby.

B. Innovation Opportunities and Challenges through Big Data on Cloud Computing

Hashem *et al.* discussed the challenges regarding the Big Data paradigms taking into account the computational infrastructure for guarantee data processing and analysis in adequate time [10]. This study presented the use of cloud computing as a solution for data storage and Hadoop technology for improving the computational response time concerning Big Data analytics. This study also showed the open research issues, where IoT represents a leading solution for acquiring large volumes of health data.

C. The Relationship Between the Body Mass Index in Pregnancy and the Risk of Stillbirth and Infant Mortality

Shin and Song presented a study about pre-pregnancy body mass index (BMI) as an essential risk-factor and its relationship with problems related to pregnancy, including considerations about newborns small and large for gestational age [11]. This study used a multivariate logistic regression analysis to determine the effect of pre-pregnancy BMI for hypertension and gestational diabetes, as well as for preterm childbirth. This research also presented a consideration about infants large and SGA concerning gestational weight gain. The results showed that the risk of several pregnancy-related complications increases with a high pre-pregnancy BMI, whereas that the risk of preterm childbirth and SGA newborns increase with a low pre-pregnancy BMI. This indicator can contribute to the identification of gestational-related problems as well as problems related to the newborn's weight.

III. Machine Learning Techniques for Predicting the Low Fetal Weight at Birth

Low birth weight is the most influential factor in the determination of neonatal morbidity and mortality. According to the World Health Organization (WHO), newborns having a birth weight below 2,500g are considered SGA [12]. This cut-off point, adopted for international comparison, is based on epidemiological observations that newborns are weighing less than 2,500g present 20 times more chances to die than newborns with more weight.

This study is a quantitative, cross-sectional, descriptive research. Data collection was acquired through the application of a form to pregnant women who suffered for some hypertensive disorder during pregnancy at the Maternity School Assis Chateaubriand of the municipality of Fortaleza, Ceará, Brazil, from May to September 2017. This period was chosen randomly, aiming to describe the reality at that moment, characterizing transversal descriptive research. The quantitative data were submitted to descriptive statistical analysis, using the MATLAB software, version R2015b. Approval was obtained from the institution's Ethics and Research Committee under No. 66929317.0.0000.5050. 205 puerperal and 32 low birth weight infants were included in the study since there were two twin births. These 32 low birth weight newborns represent 15% of total births in the period, in the study's scenario municipality. Table I presents the main intercurrences at the childbirth outcome for the fetus considered in this study.

TABLE I
PRINCIPAL OUTCOMES THAT OCCURRED AT THE BIRTH OF INFANTS OF PUBLIC MATERNITY OF FORTALEZA, CE, BRAZIL, MAY/SEP. 2017 ($n = 104$).

Intercurrences at the birth	**n**	**%**
Apgar score 5^{th} min <7	14	17.1
Neonatal ICU admission	50	61.0
Neonatal death	8	9.8
Small for Gestational Age	32	39.0

Table II presents the classes considered in this study as well as the attribute distribution of these classes in intervals.

ML algorithms can be divided into three major categories, namely, supervised, unsupervised, and reinforcement learning [13]. Decision trees (DTs) are nonparametric supervised learning methods, widely used in classification and regression tasks. In a DT each decision node contains a test for some attribute, each descendant branch corresponds to a possible value of this attribute, the set of branches are distinct, each leaf is associated

TABLE II
ATTRIBUTES CONSIDERED IN THIS STUDY RELATED TO HIGH-RISK PREGNANCY FOR FETAL WEIGHT PREDICTION AT BIRTH.

Class	Attribute
Age	]$-\infty$,20[[20,35[[35,+∞[
Gestational age at admission	[0,32[[32,45]
Diagnosis of pregnancy-specific hypertensive disease	International Statistical Classification of Diseases and Related Health Problems (ICD-10)
Risk factors	Personal and family history of pre-eclampsia; Previous pregnancies; New fatherhood; Multiple pregnancies; Interval of 10 years or more between pregnancies; Hypertension; Migraine; Diabetes; Kidney disease; Thrombophilia; Autoimmune disease.
Symptoms	Edema; Hyperreflexia; Headache; Epigastric pain; Nausea or vomiting; Blurred vision; Dizziness; Oliguria
Obesity	Normal (Body mass index (BMI) $< 30kg/m^2$) Overweight (BMI $= 25 - 29.9kg/m^2$) Morbid (BMI $> 30kg/m^2$)
Hipertension	Normal High (systolic $= 140 - 159mmHg$ and/or diastolic $= 90 - 119mmHg$) Very high (systolic $\geq 160mmHg$ and/or diastolic $\geq 110mmHg$)
Proteinuria	Absent Traces ($> 300mg/24hrs$) Severe ($> 5g/24hrs$)
Laboratory diagnosis	Bilirubin above $1.2mg/dL$ Elevation of liver enzymes (AST, TGO) $> 70U/L$ and lactic dehydrogenase (DHL) $> 600U/L$ Plaquetopenia ($< 100,000/mm^3$, with greater severity when $< 50,000/mm^3$)
Gestational age at childbirth	Before the 34^{th} gestation week After the 34^{th} gestation week

to a class and, each path of the tree, from root to leaf, corresponds to a classification rule. The criterion used to define the partitions is the utility of an attribute for the classification. It is applied, by this criterion, a specific information gain to each attribute. The attribute chosen as the test attribute for the current node is the one that has the highest information gain. From this application, a new partitioning process starts. Entropy represents the information gain calculation based on a measure used in information theory. The entropy characterizes the impurity of the data, *i.e.*, in a dataset, it is a measure of the homogeneity lack of the input data concerning its classification. Given an input set (S) that can have c distinct classes, the entropy of S is given by Equation 1.

$$Entropy(S) = \sum_{i=1}^{c} -p_i log_2 p_i \qquad (1)$$

Where p_i represents the data proportion in S that belongs to class i.

Based on the statistical learning theory, the support vector machine (SVM) algorithm seeks to solve classification problems. This method represents another category of the neural networks feed-forward, *i.e.*, networks whose outputs from the neurons of a layer feed the neurons of the next layer, not occurring the feedback. This technique, initially developed for binary classification, seeks to construct a hyperplane as a decision surface so that the separation between examples is maximal, considering linearly separable patterns. For non-linearly separable patterns, an appropriate mapping function ϕ is sought to make the mapped set linearly separable. A linear classification consists of determining a function $f : X \subseteq \mathbb{R}^n \to \mathbb{R}^n$, which assigns a label $(+1)$ if $f(x) > 0$ and (-1) otherwise. Equation 2 represents this function.

$$f(x) = \langle x \cdot w \rangle + b = \sum_{i=1}^{n} w_i x_i + b \qquad (2)$$

Where w and $b \subseteq \mathbb{R}^n \to \mathbb{R}^n$ are known as the weight and bias vector. These parameters are responsible for controlling the function and the decision rule. The learning process obtains the values of w and b from the input data.

The main idea of the K nearest neighbors (KNN) algorithm is to determine the classification label of a sample based on the neighboring samples from a training set. Two key points that must be determined for KNN application, to know, the distance metric and the value of k. For the distance metric, the most used is the Euclidean distance, described by Equation 3.

$$D=\sqrt{(p_1-q_1)^2+\cdots+(p_n-q_n)^2}=\sqrt{\sum_{i-1}^{n}(p_i-q_i)^2} \qquad (3)$$

where $P = (p_1, \cdots, p_n)$ and $Q = (q_1, \cdots, q_n)$ are two n-dimensional points. Concerning the k value, there is no single value for this constant. It varies according to the database. This study considered $k = 10$ and $k = 100$.

Recent studies have shown that ensemble classifier methods have better performance than conventional ML techniques [14]. An ensemble classifier consists of a set of individually trained classifiers whose decisions are combined. In the bootstrap aggregating algorithm the classifiers are trained independently by different training sets through the bootstrap method. To construct them it is necessary to assemble k identical training sets and replicate this training data at random to build k independent networks by re-sampling with replenishment. Next, the k networks must be aggregated by an appropriate combining method, such as the majority of votes. Algorithm 1 shows the bagging pseudo-code.

Similar to the bagging method, in the boosting algorithm, each classifier is trained using a different training set. The main difference concerning the bagging method comes from the fact that the re-sampled datasets are explicitly built to generate mutual learning, and the importance of voting is weighted based on the performance of each model, rather than the attribution of the same weight to all votes. Algorithm 2 presents the boosting pseudo-code.

Next section discusses the performance evaluation of the above described algorithms.

Algorithm 1 Bagging algorithm pseudo-code

Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$:
Number of learning rounds T.
Process: For $t = 1, 2, \cdots, T$:
(i) Constitute sets bootstrap of S_t data selecting m random examples of the training set with substitution and *(ii)* Let h_t be the training base result of the algorithm based on S_t
End.
Output: Combined classifier: $H(x) = majority(h_1(x), \cdots, h_T(x))$

Algorithm 2 Boosting algorithm pseudo-code

Input: Dataset $D = \{(x_1, y_1), (x_2, y_2), \cdots, (x_m, y_m)\}$:
Algorithm of learning base L; Number of learning rounds T.
Process: $D_1(i) = 1/m$. %Initializes the distribution of weights.
For $t = 1, 2, \cdots, T : h_1 = L(D, D_t)$;
Train the learning base h_t for D using the D_t distribution
$\epsilon_i = Pr_{i \cong D_i}[h_t(x_i \neq y_i)]$;
Measures the error of h_t
$\alpha_t = \frac{1}{2} ln \frac{1-\epsilon_t}{\epsilon_t}$
Determines the weight of h_t
$D_{t+1}(i) = \frac{D_t(i)}{Z_t} \begin{cases} exp(-\alpha_t) & if \quad h_t(x_i) = y_i \\ exp(\alpha_t) & if \quad h_t(x_i) \neq y_i \end{cases}$
Updates the distribution
$= \frac{D_t(i) exp(-\alpha_t y_i h_t(x_i))}{Z_t}$ %Normalization factor allowing D_{t+1} to be a distribution
End.
Output: $H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$

IV. Performance Evaluation and Analysis

Cross-validation or rotated estimation has become a standard method in the performance analysis of algorithms and models in ML and pattern recognition [15]. Let $S = \{(x_i, y_i)\}_{i=1}^{n}$ be a dataset, where $X = \{x_i\}_{i=1}^{n}$ are random samples of certain labeled patterns $Y = \{y_i\}_{i=1}^{n}$ of a finite set of classes, that is, the labels take values of $\Omega = \{\omega_i\}_{i=1}^{c}$. The procedure for carrying out the cross-validation consists of randomly partitioning the dataset S into k mutually exclusive folds of approximately equal sizes. Equation 4 represents this procedure.

$$S = \bigcup_{i=1}^{k} S_i \quad where \quad S_i \cap S = \emptyset \quad for \quad all \quad i \neq j \tag{4}$$

Thus, an algorithm based on a classification model is trained on the set $S \setminus S_i$ and tested on S_i, k times, also called k-fold cross-validation. This study considered $k = 10$.

The performance analysis of the various ML techniques was performed through the confusion matrix [16]. This matrix is composed by the true positives (TPs), which represents the number of positive predictions that are correct, the false positives (FPs), which represents the number of positive predictions that are incorrect. Besides, the false negatives (FNs), which represent the number of negative predictions that are incorrect, and the true negatives (TNs), which is the number of negative predictions that are correct. From the confusion matrix, the following performance measures are determined, to know, the accuracy (Acc.) and the TP rate (TPR). Equations 5 and 6 present these metrics.

$$Acc. = \frac{TP + TN}{TP + FP + TN + TN} \tag{5}$$

$$TPR = \frac{TP}{TP + FP} \tag{6}$$

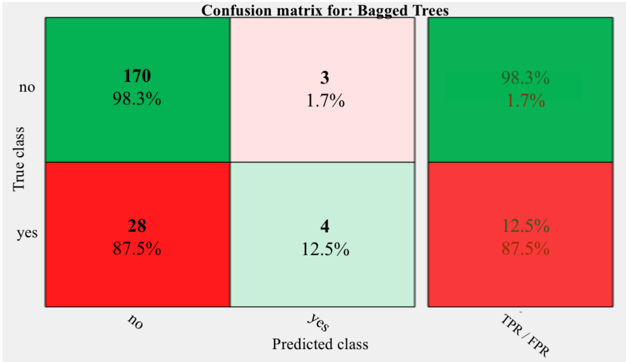

Fig. 1. Confusion matrix for the bagged trees algorithm. Percentages viewed per true class including TP and FN rates.

Table III presents the results of the confusion matrix metrics related to the main ML algorithms of the recent literature.

TABLE III
Performance Comparison Among Several Machine Learning Approaches in Pregnancy Care.

Algorithm	ACC	TPR	FPR	AUC
Tree	0.839	0.063	0.017	0.550
SVM	0.795	0.156	0.087	0.551
KNN	0.834	0.031	0.017	0.614
Boosted Trees	0.839	0.219*	0.046	0.600
Bagged Trees	0.849*	0.094	0.012*	0.636
Subspace KNN	0.834	0.094	0.029	0.675*

The performance evaluation shows that ensemble learning classifiers present superior results to decision tree and artificial neural network algorithms.

Another important metric to evaluate ML algorithms is the area under the receiver operating characteristic curve (AUC). By definition, a receiver operating characteristic (ROC) curve is the graphical representation of the sensitivity (TPR) and $1-$specificity (FPR) pairs resulting from the variation of the cut-off value along the x decision axis. The resulting graph representation is called ROC curve in the unit plane. In fact, a ROC curve is an empirical description of the ability of the diagnostic system to discriminate between two states in a universe, where each point on the curve represents a different compromise between the TP and FP rates. It can be acquired by adopting a different value of abnormality cut or critical level of confidence in the decision process. Figure 2 presents the ROC curve for the subspace KNN algorithm.

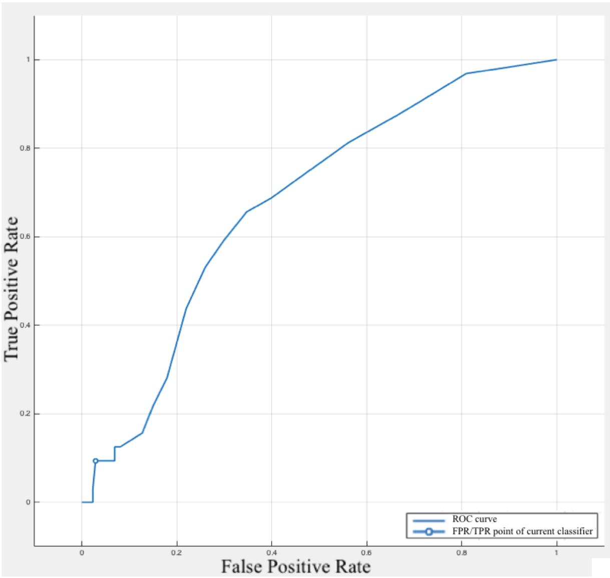

Fig. 2. Receiver operating characteristic curve for the subspace k-nearest neighbors algorithm concerning the positive class, *i.e.*, newborns that will be born small for the gestational age.

The AUC is an important indicator, representing a measure of the total precision independent of a particular threshold. An area value below the diagonal (0.5 or 50%) is not valid, because the hits and errors are in the same proportion and are due to chance. A value equal to 1.0 or 100% is not reached due to the overlap in the distribution of the proportions. In the Figure 2, the AUC for the subspace KNN classifier is equal to 0.675, *i.e.*, it reaches 67.5% of the graph area. However, there is no need to compare one test with another to evaluate whether a particular procedure is reliable or not. Table IV shows the estimative used to assess a test accuracy or the ability to identify a condition using the ROC curve correctly.

TABLE IV
ESTIMATION TO EVALUATE THE ACCURACY OF A TEST USING THE AUC.

Area Under the Curve	Classification
Above 0.90	Excellent
0.81 to 0.90	Good
0.71 to 0.80	Regular
0.61 to 0.70	Mean
0.51 to 0.60	Reproved

The found results show that classifiers based on ensemble learning present better results for the prediction of complex and high-risk situations.

V. Conclusion and Future Work

Current standards for ultrasound assessment of fetal growth can lead to misclassification of up to 15% of fetuses, considering them SGA. Growth limitation represents a sign of severe health problem, often resulting from the fetus not receiving enough nutrients or oxygen in the uterus. The understanding of many aspects of fetal growth and pathophysiology of its restriction is still weak. As clinical proposals, several models of ultrasound techniques have been developed. However, an accurate method for the disease diagnosis has not yet been found. It is known that the more initial the growth restriction, the greater the severity. ML techniques represent an essential tool to assist specialists in the early identification of this disturbance. The use of artificial intelligence techniques joined with novel technologies can reduce the high morbidity and mortality rates worldwide, especially in developing countries. Hence, this paper compared several ML techniques using a real database of pregnant women who suffered some hypertensive disorder during pregnancy. The results shown that hybrid methods based on ensemble learning are capable of efficiently predicting the expected weight of the fetus at birth.

Further works suggest the use of other combination of classifiers, especially those based on decision tree and nearest neighbors. The study of other fetal-related health restrictions is also strongly recommended.

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