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PREDICTION OF FETAL ACIDEMIA (UMBILICAL ARTERY PH < 7.1) IN SINGLETON PREGNANCY USING MACHINE LEARNING: A STUDY IN A UNIVERSITY HOSPITAL IN SOUTHERN BRAZIL

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ABSTRACT

Fetal acidemia, defined as an umbilical artery pH below 7.1, is a leading cause of intrapartum asphyxia, affecting both delivery outcomes and child development. Identifying non-invasive methods to predict fetal acidemia is crucial for improving decision-making during childbirth. This study aimed to compare various machine learning models in predicting fetal acidemia at a university hospital in southern Brazil. Data were collected from 567 patients with single pregnancies who delivered at the Hospital Geral de Caxias do Sul between 2011 and 2016. Several machine learning algorithms were developed using Python, including Extra Trees Classifier, Random Forest Classifier, Support Vector Machine, Nonlinear Support Vector Machine with RBF Kernel, Artificial Neural Networks, Gradient Boosting Machine, and Logistic Regression. The GridSearchCV function was employed to optimize model parameters. The study population was divided into two groups: Group I (397 newborns with an umbilical artery pH > 7.1) and Group II (170 newborns with an umbilical artery pH < 7.1). Significant differences were observed between the groups in variables such as parity, previous stillbirth, gestational age, diabetes, fetal presentation, type of delivery, and Apgar scores. Among the models, Artificial Neural Networks achieved the highest AUROC (0.82), followed closely by Logistic Regression (0.81). Both models demonstrated excellent precision, recall, F1-score, and accuracy. However, Logistic Regression is recommended due to its lower computational demands. This study highlights the potential of machine learning models in providing a non-invasive method to predict fetal acidemia, aiding healthcare professionals in clinical decision-making.

Keywords: Fetal acidemia; Umbilical artery pH; Artificial intelligence.

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INTRODUCTION

The main cause of intrapartum asphyxia is fetal acidemia, which is diagnosed by the acid-base status in the umbilical artery. Despite the scientific progress in the area, hypoxic events at birth still cause a series of morbidities and mortality among newborns (PERVEEN; KHAN; ALI; RABIA, 2015; KAPAYA; WILLIAMS; ELTON; ANUMBA, 2018). Research suggests that an umbilical artery pH lower than 7.1 can be associated with poor outcomes (CAHILL, 2015). In such cases, there is a higher probability of cerebral paralysis, intracranial hemorrhage, respiratory distress syndrome, and convulsion (CAHILL, 2015; LEE , *et al*., 2020; DILDY, 2005).

Although the umbilical artery pH is crucial to identify poor outcomes, it is not a routine procedure in all hospitals. Due to the risks, it has been done only for high-risk pregnancies (NATIONAL INSTITUTE FOR HEALTH AND CARE EXCELLENCE, 2014; ROYAL COLLEGE OF OBSTETRICIANS & GYNAECOLOGISTS, 2015). Some studies even support a delayed cord clamping of two or three minutes to allow more blood from the placenta to flow to the newborn (ROYAL COLLEGE OF OBSTETRICIANS & GYNAECOLOGISTS, 2015; MCDONALD; MIDDLETON; DOWSWELL; MORRIS, 2014). However, it would be relevant to have that data for all newborns given its importance (MALIN; MORRIS; KHAN KS, 2010).

The area of obstetrics has some limitations in diagnosing methods because the interactions between the fetus and the pregnant woman present high complexity. Nevertheless, an increasing number of researchers are applying machine learning to predict intrapartum outcomes (EMIN, *et al*., 2019). We aimed to develop classification machine learning models to predict, through clinical variables, if the umbilical artery pH will be lower than 7,1.

MATERIALS AND METHODS

The methodology employed for the selection, categorization, and processing of variables utilized in the study. Variables were chosen based on their clinical importance and their presence in hospital records. Categorical variables, such as fetal presentation and delivery type, were converted into numerical codes to streamline processing by machine learning models. Continuous variables, including maternal age and body mass index, were standardized to maintain consistency in scale. Furthermore, missing data were handled through statistical imputation, employing either the mean or mode, depending on the variable type, to reduce the potential impact of data gaps on the analysis.

This cross-sectional study analyzed retrospective data from women who gave birth from 2011 to 2016 in the Gynecological/Obstetric and Neonatology Departments of the Hospital Geral de Caxias do Sul. The inclusion criterion was singleton pregnancy while excluding records with missing data.

The population was allocated into two groups: Group I containing newborns with an umbilical artery pH higher than 7.1, and Group II presenting newborns with umbilical artery pH lower than 7.1 (fetal acidemia). Group I was selected according to the newest data to compromise 70% of records while Group II comprises 30%.

The following variables were reviewed for each group: maternal age, parity (number of children), previous neonatal death, previous stillbirth, previous term stillbirth, previous cesarean section, gestational age (weeks), diabetes (composed by type-1, type -2 and gestational diabetes), body mass index (kg/m²), fetal presentation (cephalic, breech, shoulder), type of delivery (vaginal, cesarean-section, forceps), fetus sex, and Apgar score in the first and fifth minute of life.

Statistical analysis was performed using the software IBM SPSS. The Student's t-test and Mann-Whitney test were used for numerical variables while the Chi-square and Fisher's tests were used for categorical variables. To estimate the risks, a p-value less than 0.05 was considered statistically significant.

We also developed the following machine learning algorithms using Python to predict the risk of fetal acidemia: Extra Trees Classifier (ETC), Random Forest Classifier (RFC), Support Vector Machine (SVM), Nonlinear SVM with RBF Kernel (NSVM), Artificial Neural Networks (ANN), Gradient Boosting Machine (GBM), and Logistic Regression (LG). The data were stratified into 70% for training and 30% for testing those models. After that, we used the GridSearchCV function to find the best parameters of each model for optimization.

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RESULTS

This study was carried out by using records of 567 pregnancies. The contribution from Group I was 397 samples which were selected according to the newest data to comprise 70% of total records. During the time of the study, 170 cases from Group II were identified, all of which were included to comprise the other 30%.

Table 1 demonstrates the characteristics of the population included in the study. The statistical analysis showed a significant difference between Group I and Group II in the following variables: parity (0.98 ± 1.251 vs. 0.75 ± 1.110), previous stillbirth, gestational age (38.35 ± 2.384 weeks vs. 38.75 ± 2.726), diabetes (no diabetes n=376, 95.71% vs n=146, 85.88%; mellitus type I n=0 vs n=2, 1.18%; mellitus type II n=0 vs n=3, 1.76%; gestational n=21, 5.29% vs. n=19, 11.18%), fetal presentation (cephalic n=373, 93.95% vs n=163, 95.88%; breech n=24, 6.05% vs n=5, 2.94%; shoulder n=0 vs n=2,1.18%), type of delivery (vaginal n=202, 50.88% vs. n=78, 45.88%; forceps n=175, 44.08% vs. n=67, 39.41%; cesarean-section n=20, 5.04% vs. n=25, 14.71%), Apgar in the first minute lower than four (n=11; 2,77% vs. n=35; 20,59%)) and Apgar in the fifth minute lower than seven (n=2; 0,50% vs. n=15; 8,82%).

Table 1. Distribution of variables related to the umbilical artery pH.

Variable	Group I *n = 397*	Group II *n = 170*	p-value
Maternal age [a]	24.88 ± 6.73	24.88 ± 6.85	0.953
Parity [b]	1	0	0.016
Previous neonatal death [b]	0	0	1.000
Previous stillbirth [b]	0	0	0.049
Previous term stillbirth [b]	0	0	0.513
Previous premature stillbirth [b]	0	0	0.142
Previous cesarean section [a]	0.40 ± 0.80	0.41 ± 0.73	0.884
Gestational age (weeks)[a]	38.35 ± 2.38	38.75 ± 2.73	0.001
Diabetes			0.000
No diabetes	376 (94.71%)	146 (85.88%)	-
Mellitus type I	0 (0%)	2 (1.18%)	-
Mellitus type II	0 (0%)	3 (1.76%)	-
Gestational	21 (5.29%)	19 (11.18%)	-
Body mass index [a]	30.29 ± 6.299	31.35 ± 6.356	0.070
Fetal presentation			0.032
Cephalic	373 (93.95%)	163 (95.88%)	-
Breech	24 (6.05%)	5 (2.94%)	-
Shoulder	0 (0%)	2 (1.18%)	-
Type of delivery			0.000
Vaginal	202 (50.88%)	78 (45.88%)	-
Forceps	175 (44.08%)	67 (39.41%)	-
Cesarean	20 (5.04%)	25 (14.71%)	-
Fetus sex			0.166
Feminine	198 (49.87)	74 (43.53)	-
Masculine	199 (50.13)	96 (56.47)	-
1-minute Apgar <4	11(2,77%)	35 (20,59%)	0.000
5-minute Apgar <7	2(0,50%)	15 (8,82%)	0.000

Group I: newborns with an umbilical artery pH higher than 7.1; Group II: newborns with an umbilical artery pH equal to or lower than 7.1; [a] mean ± standard deviation, [b] median.

Table 2 shows the results obtained by applying machine learning algorithms to predict fetal acidemia. The F1-score is a harmonic mean between precision, also known as sensibility, and recall, also known as specificity.

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The table also indicates the overall accuracy of the models as well as the area under the receiver operating characteristic curve (AUROC).

Table 2. Machine Learning (before optimization).

Model	Accuracy	AUROC	Precision	Recall	F1-score
Extra Trees Classifier	0.75	0.75	0.78	0.88	0.83
Random Forest Classifier	0.72	0.76	0.78	0.83	0.80
Support Vector Machine	0.79	0.80	0.78	0.96	0.86
Nonlinear SVM with RBF Kernel	0.67	0.80	0.67	1.00	0.80
Artificial Neural Networks	0.78	0.82	0.79	0.93	0.85
Gradient Boosting Machine	0.74	0.76	0.79	0.84	0.81
Logistic Regression	0.79	0.81	0.79	0.94	0.86

Table 3 shows the metrics obtained after applying the GridSearch function for the optimization of the models.

Table 3. Machine Learning (after optimization).

Model	Accuracy	AUROC	Precision	Recall	F1-score
Extra Trees Classifier	0.74	0.76	0.78	0.86	0.82
Random Forest Classifier	0.77	0.77	0.81	0.86	0.83
Support Vector Machine	0.79	0.80	0.78	0.96	0.86
Nonlinear SVM with RBF Kernel	0.71	0.71	0.70	0.97	0.82
Artificial Neural Networks	0.79	0.82	0.78	0.95	0.86
Gradient Boosting Machine	0.74	0.78	0.78	0.85	0.81
Logistic Regression	0.80	0.81	0.79	0.95	0.87

Table 4 presents the AUROC of each model before and after optimization.

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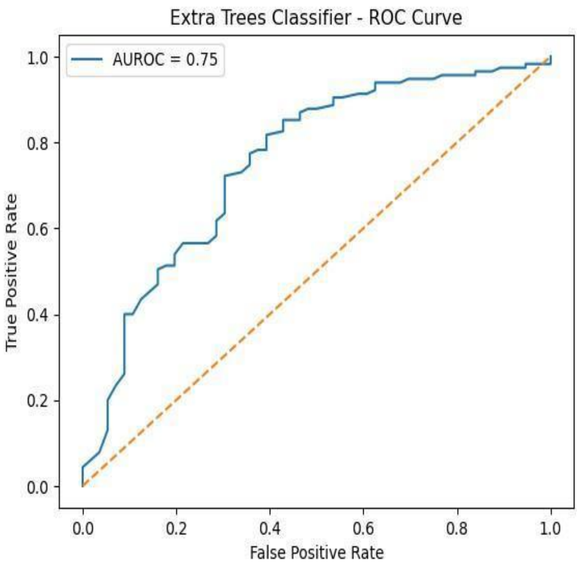
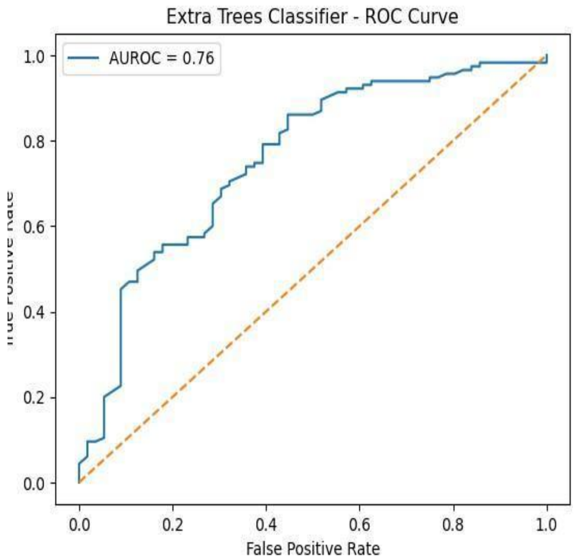
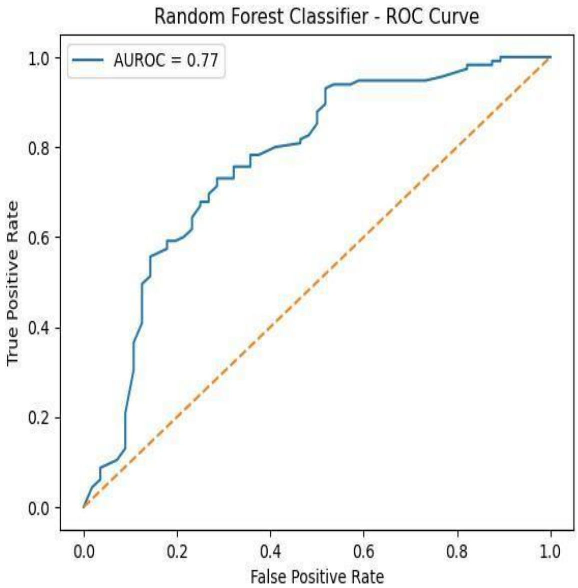
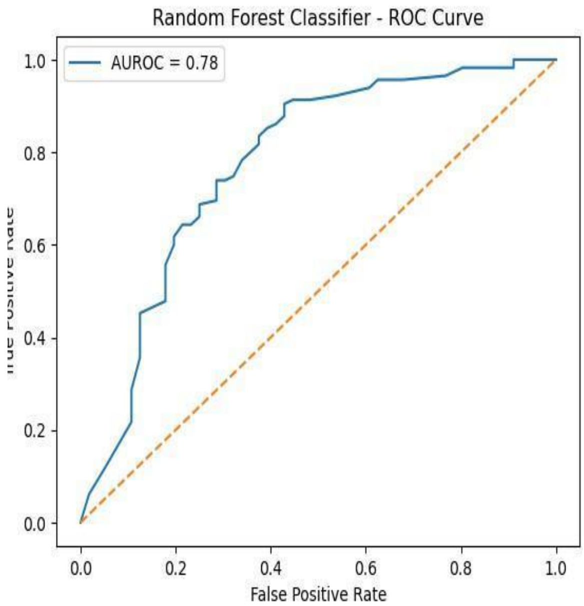
Table 4. AUROC before and after optimization.

Model	AUROC before optimization	AUROC after optimization
Extra Trees Classifier		
Random Forest Classifier		

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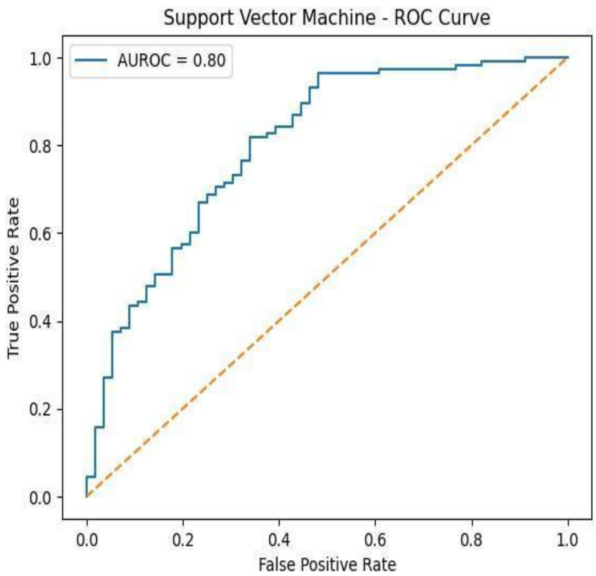
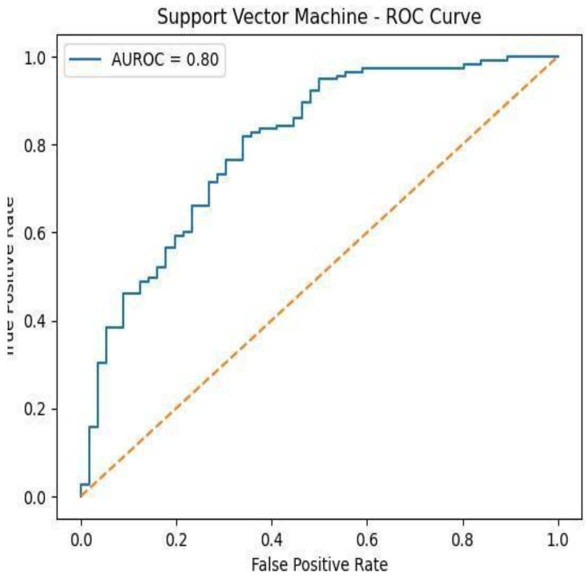
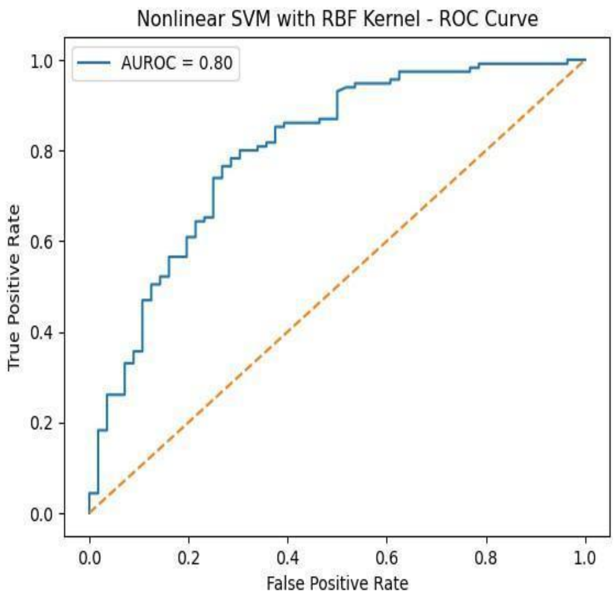
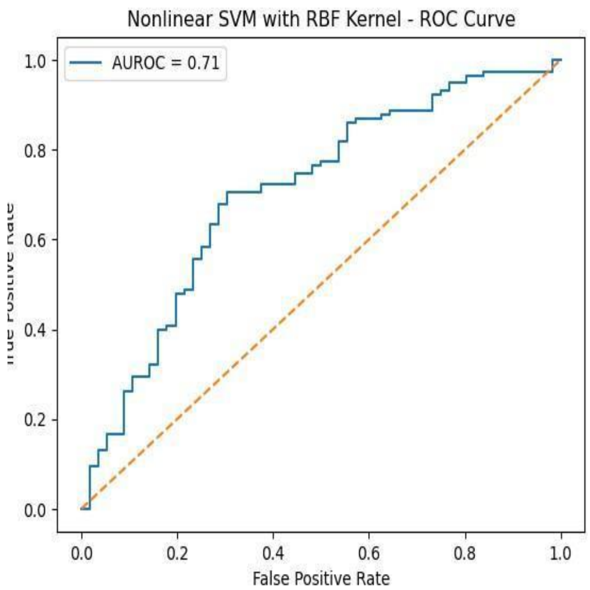
Support Vector Machine		
Nonlinear SVM with RBF Kernel		

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<table>
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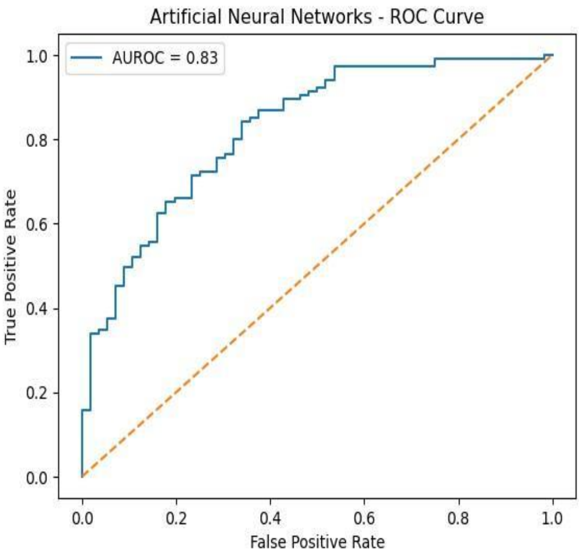
<td>Artificial Neural Networks</td>
<td>
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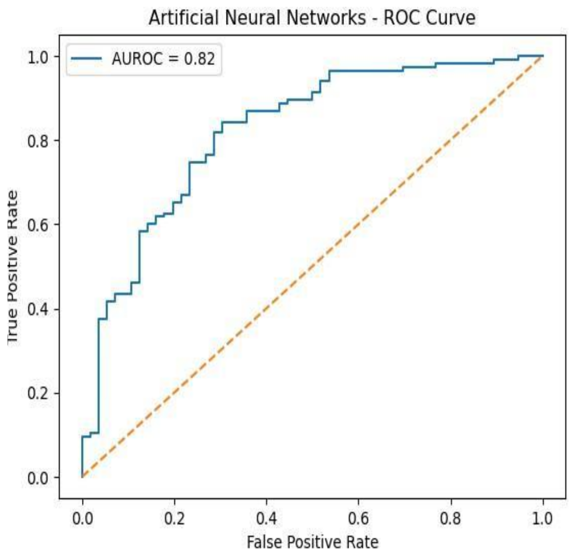
<td>
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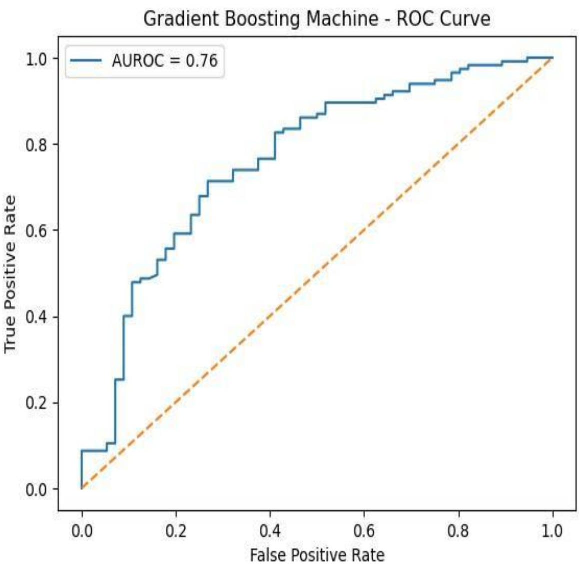
<tr>
<td>Gradient Boosting Machine</td>
<td>
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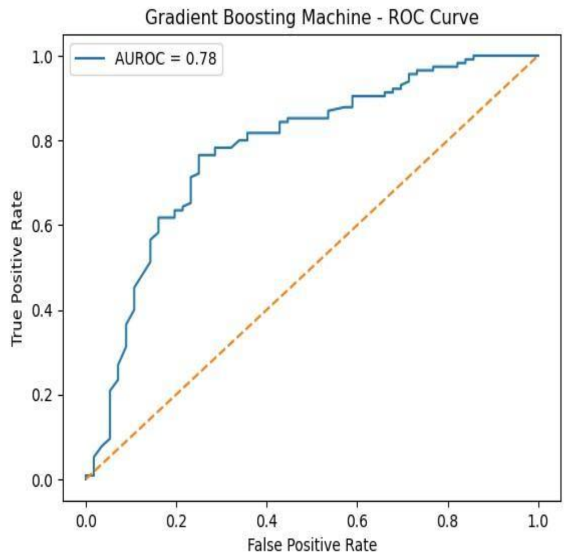
<td>
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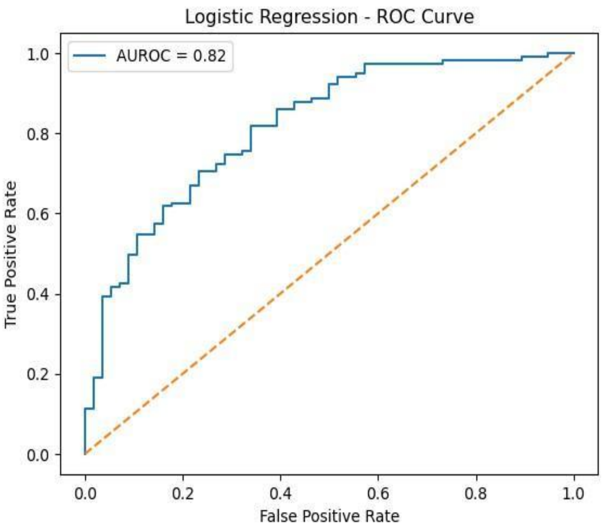
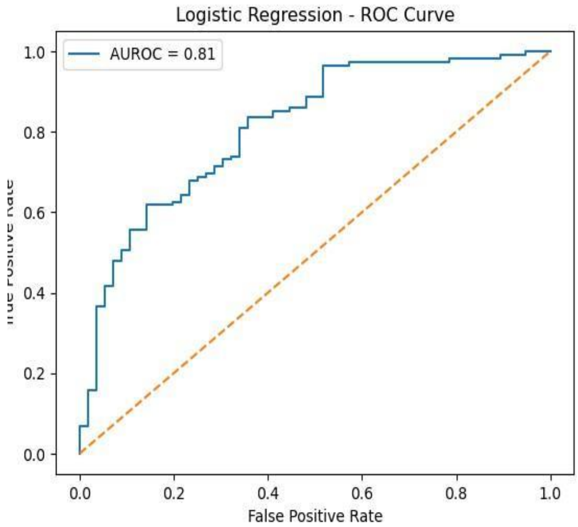
Logistic Regression		

The ANN was the model that presented the best performance among the algorithms developed. The AUROC (0.82) shows an excellent balance between true positive and false positive rates. In addition, the model has a high precision (0.78), recall (0.95), and F1-score (0.86). This is the best model for this database given its accuracy (0.79) and further metrics.

The second model with the highest metrics was the LR. Even though its AUROC (0.81) is slightly lower than the one obtained by applying ANN, it also had an outstanding precision (0.79), recall (0.95), F1-score (0.87), and accuracy (0.80). Thus, it can identify correctly both cases when the pH is higher or equal/lower than 7.1. It can be an alternative to ANN if considering the training time and model complexity.

This study has some limitations that must be acknowledged. Firstly, the data used were collected from a single hospital, which may introduce biases related to regional practices and patient profiles. Secondly, challenges related to generalization arise, as the models may not perform equally well in other clinical settings without proper retraining on local data. Finally, implementing these machine learning tools in real-world scenarios requires addressing practical issues, such as integration with electronic health records and ensuring user-friendliness for healthcare professionals.

COMMENT

Even though there are recommendations for an acid-base status analysis only on specific cases, its importance is imperative to evaluate fetal viability (THORP, *et al*., 1996). This study proposes a non-invasive method to predict fetal acidemia not only in high-risk pregnancies. Another research developed a statistical model to predict the umbilical artery pH given some clinical variables and the fetal cardiac rate (RAMANAH, *et al*., 2018). This paper differs from other similar studies on the aspect of the clinical variables used as well as on the machine learning models developed.

The Apgar score, when combined with the umbilical artery pH, can help identify other risks; but it cannot identify fetal acidemia when evaluated separately. Thus, it is crucial to have both of those parameters (SABOL; CAUGHEY, 2016). In addition, studies show that the gestational age, fetus sex (SKIÖLD, *et al*., 2017), obesity (RIMSZA, *et al*., 2019), pre-gestational diabetes (KAPAYA, *et al*., 2018), previous neonatal deaths, maternal age equal to or higher than thirty-five years old, maternal low weight and height, high parity rates, and previous cesarean delivery (DILDY, 2005), can lead to a lower umbilical artery pH.

Healthcare has shown progress in diverse areas related to technology and there are plenty of opportunities to use math to solve problems (TUNC; ALAGOZ;

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BURNSIDE, 2014; SANCHEZ, *et al*., 2016; WANG, *et al*., 2016). This study enabled collaborative work between healthcare and engineering professionals to develop a tool to help with decision-making. Studies are using the same algorithms used in this paper to predict outcomes such as bleeding within twenty-four hours after vaginal delivery (AKAZAWA, *et al*., 2021) stillbirth (MOHAMMADI, *et al*., 2022), pre-eclampsia (MANOOCHEHRI, *et al*., 2021), depression, and perinatal anxiety (JAVED, *et al*., 2021), among others. In addition, they used the same parameters to evaluate and compare the methods.

Artificial intelligence has been broadly used in research in the area of obstetrics and gynecology, with non-symbolic machine learning representing 59% of the studies. However, 86% of the studies used only one database without clinical validation. The biggest challenges are related to process standardization, bioethics, and process validation (DHOMBRES, *et al*., 2022). The next research proposed is to develop a real-time application for testing and future use of this tool. Studies indicate that ML models also should be tested specifically for each study case to avoid high rates of false negatives (FITZPATRICK; DOHERTY; LACEY, 2020; SCARDONI, *et al*., 2020). Thus, to use this system in other hospitals, it is also necessary to train the algorithms again using their database to ensure accuracy. Aside from the technical requirements, it is necessary a change in the culture and behavior of healthcare institutions to sustain long-term improvements (FITZPATRICK; DOHERTY; LACEY, 2020).

CONCLUSION

Machine learning has been used in healthcare settings to assist professionals in decision-making. Specifically, in obstetrics, several researchers are applying it to diverse contexts. The umbilical artery pH is a crucial characteristic to be identified in newborns, and this study proposes a non-invasive method to access it. Among the algorithms proposed, the ANN and RL presented the best performance in identifying both groups to predict fetal acidemia; however, we recommend using Logistic Regression because it requires less computational capability. Even though there are some challenges, there are many opportunities to develop robust models for future use in healthcare facilities.

Additionally, as a proposal for future work, the implementation of tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) is suggested. These techniques provide interpretable explanations for the predictions made by machine learning models, aiding healthcare professionals in understanding how each variable contributes to the predicted outcomes. The use of these tools can enhance confidence in the clinical application of the models by highlighting the most relevant factors in predicting fetal acidemia. Despite their significance, the practical implementation of these tools requires additional computational resources and time, which exceeded the scope of this study. Additionally, For the application of the proposed model, we suggest a clinical validation plan that includes fundamental steps to ensure its effective integration into healthcare environments. Firstly, we recommend conducting an initial assessment of existing healthcare systems to identify key points of technical integration, such as compatibility with hospital platforms and electronic health record systems. Subsequently, we suggest developing clinical validation protocols based on real samples, adhering strictly to ethical and safety standards. Additionally, it will be essential to implement a comprehensive training program to prepare healthcare teams for the use of the model, focusing on interpreting results and supporting decision-making. We also propose establishing a continuous monitoring process to collect feedback from involved teams and patients, allowing iterative adjustments to improve the model's performance. Finally, we recommend designing a scalability plan, adapting the model for diverse clinical contexts and promoting its acceptance through educational and awareness initiatives about its benefits.

For the practical application of the model, we propose balancing performance and computational complexity. While Artificial Neural Networks demonstrated slightly superior metrics, their greater complexity and demand for computational resources may hinder their implementation in clinical environments with limited infrastructure. Conversely, we suggest using Logistic Regression, which showed similar performance metrics and offers significant advantages in terms of simplicity in training and deployment. This approach will enable faster integration with healthcare systems, reduce the need for advanced resources, and facilitate team training. Therefore, Logistic Regression could be a pragmatic choice to maximize the applicability and clinical impact of the proposed model.

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