RESEARCH PAPER

Determinants of Neonatal Respiratory Distress in a Middle-Income Country: Classical and Ai-Based Analyses from a Retrospective Cohort Study

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ABSTRACT

Background: Neonatal respiratory distress (NRD) is a major contributor to neonatal morbidity and mortality in middle-income countries.

Objective: To identify independent risk factors for NRD using classical logistic regression and to explore multivariate interactions using a Classification and Regression Tree (CART) model and correlation heatmaps.

Methods: A retrospective cohort study was conducted from January 2023 to December 2024 at the National Reference Center for Neonatology in Rabat. During the study period, 630 newborns who met the inclusion criteria were included in 2 groups: neonates with respiratory distress (n=421) and neonates without respiratory distress (n=209). The identification of risk factors was carried out using bivariate as well as multivariate analyses and Python (Scikit-learn, Seaborn) for CART modeling and heatmap visualization.

Results: 630 births were collected during this period. Neonatal respiratory distress was multifactorial. Statistical analysis could reveal mostly maternal anemia (OR = 8.10; CI95 (7.52-43.55); $p < 0.05$), diabetes (OR = 3.65; CI95 (1.98-6.72); $p = 0.001$), caesarean section (OR = 4.23; CI95 (1.54-11.59); $p = 0.001$), prematurity (OR = 2.45; CI95 (1.41-4.26); $p = 0.01$) as significant independent predictors of NRD (all $p < 0.05$). The CART model achieved perfect test set performance (AUC = 1.00; sensitivity = 100%; specificity = 100%), suggesting potential overfitting. A Spearman correlation heatmap confirmed strong associations ($\rho > 0.88$) between NRD and all predictors.

Conclusion: Both classical and AI-based methods converged in identifying relevant clinical predictors. Interpretable AI models may enhance neonatal risk stratification, especially in resource-limited contexts.

Keywords: Neonatal respiratory distress, logistic regression, CART, heatmap, machine learning.

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Introduction

Neonatal respiratory distress (NRD) remains a leading cause of neonatal morbidity and mortality, especially in preterm infants and in low- and middle-income countries (LMICs) where access to surfactant therapy and advanced respiratory support is limited (1). Respiratory distress syndrome (RDS), the main form of NRD, results from pulmonary surfactant deficiency in

infants born before 34 weeks (2). Despite the benefits of surfactant therapy and antenatal corticosteroids, maternal and perinatal factors—such as cesarean section, anemia, gestational diabetes, abnormal amniotic fluid, and neonatal resuscitation still influence incidence (3 ,4).

Predictive factors of NRD can be grouped into maternal, delivery-related, and neonatal categories (5). Maternal disorders (hypertensive disease, diabetes, premature membrane rupture, chorioamnionitis) and elective cesarean delivery without labor significantly increase risk (5–7).

Traditional statistical models like logistic regression help identify associations but struggle with complex nonlinear interactions. Machine learning (ML) techniques, particularly Classification and Regression Trees (CART), offer better detection of multifactorial pathways and easier clinical interpretation (8,9). Correlation heatmaps further reveal interrelations between predictors, confirming independence of associations (10).

Recent studies combining ML and conventional methods show promising accuracy in predicting neonatal complications (11). However, no prior research has jointly applied logistic regression, CART, and correlation visualization to study NRD determinants in a Moroccan cohort. This study fills that gap by integrating classical and ML-based analyses to enhance understanding and prediction of NRD, ultimately supporting precision neonatal care in LMICs

1. Study Design and Population

This was a retrospective analytical study conducted at the National Reference Center for Neonatology and Nutrition, based at the Children's Hospital of Rabat, a tertiary-level facility and one of Morocco's major neonatal care centers. The study covered the period from January 1, 2023, to December 31, 2024.

The population consisted of all newborns hospitalized for neonatal respiratory distress (NRD) within the early neonatal period (first seven days of life). A consecutive convenience sampling method was used. Only records that were complete and met eligibility criteria were included.

2. Inclusion and Exclusion Criteria

Inclusion criteria: All neonates (symptomatic or asymptomatic) admitted for clinical management of neonatal respiratory distress during the first week of life.

Exclusion criteria: Newborns with congenital malformations.Respiratory distress due to surgical etiologies (e.g., congenital diaphragmatic hernia).Incomplete or missing essential data in the clinical file.

4. Data Collection /Study variables

Data collection was carried out by a documentary technique consisting of studying the medical records of each neonate. All data were entered using an information sheet containing the following sections: Maternal and obstetrical characteristics , Characteristics of the newborn, Evaluation of the patient .

Dependent variable: neonatal respiratory distress

Independent variables:

Socio-demographic characteristics: age, residence, marital status, educational and socioeconomic status of the mother, gestational age and area of origin ;Obstetrics-related factors: gravidity, parity, current mode of delivery.

Newborn characteristics (sex, birth weight, Apgar score,Silverman score, and time to respiratory distress> or <3 hours.

- Immediate resuscitation at birth.
- Amniotic rupture.
- Maternal pathologies during pregnancy (gestational diabetes, pre-eclampsia, goiter, asthma and anemia)

Evaluation of the severity is based on a Silverman score, which is composed of inspiratory and expiratory categories of movements.

The scale of the Silverman score ranges from 0 to 2:

- Neonatal moderate respiratory distress corresponding to Silverman ≤4
- Intense Neonatal Respiratory Distress corresponding to Silverman between 4 – 6
- Very intense Neonatal Respiratory Distress corresponding to Silverman >6

Definitions of used terms:

- Neonatal respiratory distress is defined by the presence of at least one of the following elements: abnormal respiratory rate (tachypnea > 60 breaths/min; bradypnea < 30 breaths/ min; respiratory pauses, or apnea) or signs of labored breathing (expiratory grunting, nasal flaring, intercostal recessions, xyphoid recessions or thoracoabdominal asynchrony) .
- Silverman's score = A score greater than 7 indicates that the baby is in respiratory failure.
- resuscitation at birth at birth: refers to the time it takes to seek care after the onset of labor that is longer than 1 hour.
- Primimarous: a woman pregnant for the first time
- Multiparous: a woman who has had multiple births
- Premature rupture of membranes (PROM) is a rupture (breaking open) of the membranes (amniotic sac) before labor begins.

6. Statistical Analysis : All variables were recorded and coded in Excel and then analyzed using SPSS 25.0

and Python 3.11. A two-step analytical approach was used:

Classical statistics: In this study, both descriptive and analytical approaches were applied to examine the associations between various maternal and neonatal factors and the risk of Neonatal Respiratory Distress (NRD). Descriptive statistics (means, SD, medians, frequencies).Univariate analysis using chi-square and Student's t-tests.Binary logistic regression for multivariate modeling.

Machine learning techniques: Descriptive statistics were computed for all key variables used in the CART model and heatmap visualization, including means, standard deviations, and observed ranges. Pearson correlation coefficients were calculated to evaluate the strength of linear associations with NRD.

A Classification and Regression Tree (CART) model was developed to explore multivariate patterns and identify the most influential variables contributing to NRD. The feature importance metrics derived from the CART analysis provided additional insight into variable relevance in classification tasks.

Statistical analysis was conducted using Python libraries including Scikit-learn, Pandas, and Seaborn. Significance threshold was set at $p < 0.05$.

7. statement of ethical clearance : The authors take full responsibility for the study design, data collection, analysis, interpretation, writing, and approval of the final manuscript. Ethical Compliance: This study complies with the Helsinki Declaration and was approved by the Biomedical Research Ethics Committee (CERB) of Mohammed V University, Rabat (Approval No. C64/20).

Results : We included 630 newborns, among whom 421 had neonatal respiratory distress (NRD) symptoms NRDS. Table1 shows that the median maternal age was 35 years (Q1-Q3: [22; 36]). The distribution according to educational level was dominated by illiteracy and secondary education with respective percentages of 48.2% and 44.2%, $p<0.05$. On the other hand, the university level was only 7.6% of the population. The mean gestational age of the newborns was 36.8 ± 8.86 gestational weeks; socioeconomic status was low in 54.2% of the cases and medium in only 45.8%, $p<0.05$.

Table 1. Patients' characteristics :

Patients' characteristics	**Neonates without respiratory distress (N=209)**	**Neonates with respiratory distress (N=421)**	**p**
Age (year)			
< 21	(577) 36.8	(42) 10.0	< 0.05 *
21–35	(34) 16.3	(126) 29.9	
> 35	(98) 46.9	(253) 60.1	
Parity			
Primiparous	(139) 66.5	(216) 51.3	< 0.05 *
Multiparity >2	(70) 33.5	(205) 48.7	
Provenance			
outborn	(86) 41.1	(212) 50.4	< 0.05 *
inborn	(123) 58.9	(209) 49.6	
Socioeconomic Level (MAD)			
<3000	(49) 23.4	(228) 54.2	< 0.05 *
>3000	(160) 76.6	(193) 45.8	
Level of education			
Primary school	(74) 35.4	(203) 48.2	< 0.05 *
Secondary school	(118) 56.5	(186) 44.2	
university	(17) 8.1	(32) 7.6	
antenatal consultations			
< 3	(196) 93.8	(365) 86.7	< 0.0

			5 *
≥3	(13) 6.2	(56) 13.3	
Preterm or Term (wk)			
Preterm	(58) 27.8	(228) 54	< 0. 0 5 *
28–35			
Term	(126) 60.3	(60) 14.3	
36–40			
Term >40	(25) 12.0	(133) 31.6	

* Significant (P < 0.05). Quantitative variables were expressed as average ± standard deviation and qualitative variables were expressed in numbers and percentages

Table 2 indicates that among 421 neonates with neonatal respiratory distress, 190 were female and 231 were male, with a sex ratio of 1.21; the sex of the neonate had no effect on neonatal respiratory distress in our study (p=0.62),

The mean birth weight was 3000g (Q1-Q3: [2100; 4050]).The cesarean section prevailed in 80.5% of cases, with a significant statistical difference p<0.05; early rupture of membranes >12 hours was 84.1% and aspect of amniotic fluid (55.1%) p<0.05

Table 2. Obstetrical neonatal Characteristics and associated maternal pathologies

	Category	**Neonates without respiratory distress N=219 (%)**	**Neonates with respiratory distress N=421 (%)**	**p**
Obstetrical Characteristics				
Delivery mode	Low way	75 (35.9)	82 (19.5)	< 0. 0 5 *
	Cesarean	134 (64.1)	339 (80.5)	
Membrane rupture (hour)	> 12	189 (90.4)	354 (84.1)	< 0. 0 5 *
	<12	20 (9.6)	67 (15.9)	
Amniotic fluid	Clear	187 (89.5)	189 (44.9)	< 0. 0 5 *
	Meconium	22 (10.5)	232 (55.1)	
Associated maternal pathologies				
Asthma		196 (93.8)	378 (89.8)	0. 0 9
Goiter		199 (95.2)	391 (92.9)	0. 2
Preeclampsia		154 (73.7)	274 (65.1)	0. 0 2 *
Infections		173 (82.8)	275 (65.3)	< 0. 0 5 *
Maternal Anemia		197 (94.3)	241 (57.2)	< 0. 0 5 *
Gestational Diabetes		123 (58.9)	377 (89.5)	< 0. 0 5 *
Neonatal characteristics				
Birth weight				

	Normal	129 (61.7)	57 (13.5)	<0.05*
	Hypotrophy	51 (24.4)	229 (54.4)	<0.05*
	Macrosomia	29 (13.9)	135 (32.1)	<0.05*
	Prematurity	56 (26.8)	230 (54.0)	<0.05*
Silverman score	>4	209 (100.0)	1 (0.2)	
	4-6		103 (24.5)	0.05*
	>6		317 (75.3)	
*Significant (P < 0.05). Quantitative variables were expressed as average ± standard deviation and qualitative variables were expressed in numbers and percentages				

The main maternal and neonatal pathologies associated with respiratory distress were anemia (p<0.05), pre-eclampsia (p=0.02), maternal infection (p<0.05) and gestational diabetes
(p<0.05). The main identified causes of respiratory distress were transitory tachypnea (16.5%), maternal-fetal infection (19.6 %), hyaline membrane disease (30. 1%) and prematurity (54%).

Multiple regression statistical analysis primarily incriminated anemia (OR = 18.10; 95 CI (7.5 -43.55); p <0.05), diabetes (OR= 3.65; 95 CI (1.98-6.72); p = 0.001), cesarean section (OR =
4.23; 95 CI (1.54-11.59); p = 0. 001), prematurity (OR = 2.45;95 CI (1.41-4.26); p = 0.01), appearance of amniotic fluid (OR= 27.9; 95 CI (13.46-55.34); p < 0.005); premature rupture of membranes (OR = 5.40; 95 CI (2.58-11.29); p < 0.05), and early resuscitation at birth (OR = 30.95; 95 CI (13.65-70.13); p < 0.05) (Table 3).

Table 3. Multivariate analysis of risk factors for neonatal respiratory distress

*Significant, OR: Odds ratio; a p-value < 0.05 was considered significant. PROM: Premature rupture of membranes. AFA: amniotic fluid appearance

In addition to classical modeling, we used a machine learning approach with CART (Classification and Regression Tree) to refine risk profiles.

Figure 1 presents a decision tree generated using the CART (Classification and Regression Tree) algorithm, based on real data from the cohort. This tree identifies combinations of maternal and neonatal factors most strongly associated with the occurrence of neonatal respiratory distress (NRD).

The primary discriminating factor (root node) is the need for resuscitation at birth. This variable aligns with the pathophysiology of NRD, as it reflects an immediate respiratory failure requiring active intervention. Among neonates who required resuscitation, the model shows that NRD risk is significantly influenced by maternal anemia, abnormal amniotic fluid appearance (AFA), prematurity, and gestational diabetes.

Among neonates who did not require resuscitation, maternal anemia and gestational diabetes still emerged as important predictors. The overall tree structure highlights the hierarchical interaction between maternal and neonatal factors, showing that certain combinations (e.g., resuscitation + AFA + prematurity) are particularly associated with high NRD risk.

Beyond its predictive value, the tree also offers direct clinical interpretability. It enables risk stratification at birth and can help identify newborns who may benefit from enhanced respiratory monitoring during the immediate neonatal period.

	regression Parametre B	*OR IC 95*	*p*
Cesarean	***1,442***	*4,23 [1,54 ;11,59]*	*,005**
Prematurity	***0,899***	*2,45 [1,41 ;4,268]*	*,001**
Gestational-Diabete	***1,296***	*3,65[1,98 ;6,727]*	*,000**
Maternal anemia	***2,896***	*8,10[7,52 ;43,55]*	*,000**
Resuscitation at birth	***3,432***	*30,95[13,65 ;70,13]*	*,000**
A F A	***1,687***	*5,40 [2,58 ;11,29]*	*,000**
PROM	***3,307***	*27,29[13,46 ;55,34]*	*,000**

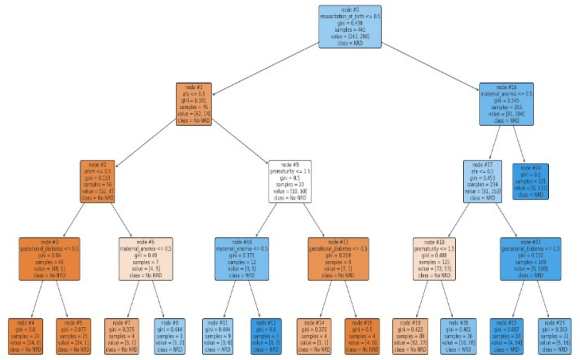

Figure 1. Clinical Decision Tree Predicting Neonatal Respiratory Distress Risk Based on Maternal and Neonatal Variables

The CART decision tree identifies key predictive pathways for NRD. Neonates requiring resuscitation at birth have the highest likelihood of developing NRD. If amniotic fluid is also abnormal (e.g., meconium-stained or infected), the risk increases significantly. In the absence of resuscitation, maternal anemia and diabetes help stratify the remaining risk, showing their combined predictive relevance.

Figure 2 displays the Spearman correlations between neonatal respiratory distress (NRD) and various maternal and neonatal factors. The coefficients (ρ) represent the strength and direction of the association between each variable and the occurrence of NRD.

The results show that resuscitation at birth has the highest correlation with NRD (ρ = 0.46), reflecting a direct link between immediate respiratory failure and the need for assisted ventilation. Abnormal amniotic fluid appearance (AFA), such as meconium-stained fluid, is also strongly correlated (ρ = 0.43), indicating increased risk of aspiration or infection.

Maternal anemia shows a moderate association with NRD (ρ = 0.38), likely due to chronic fetal hypoxia. Prematurity (ρ = 0.26) and cesarean delivery (ρ = 0.18) show weaker correlations, suggesting that their effects on NRD are mediated through other mechanisms.

Gestational diabetes is negatively correlated with NRD (ρ = –0.36), possibly reflecting better antenatal monitoring and planned deliveries that reduce respiratory risk. Finally, prolonged rupture of membranes (PROM) shows only a weak correlation (ρ = 0.09).

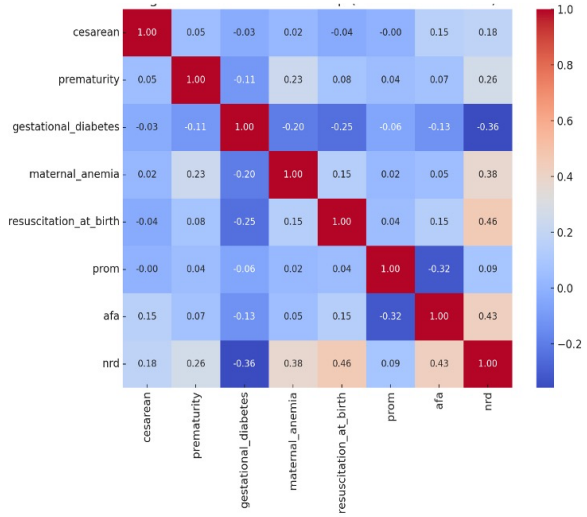

Figure 2. Correlation Heatmap of Neonatal Respiratory Distress and Clinical Risk Factors

Discussion

In this comprehensive study, we combined classical statistical methods and machine learning approaches to identify predictors of neonatal respiratory distress (NRD). The high prevalence of NRD observed in our cohort (66.8%) likely reflects the characteristics of the population managed at a university hospital, where complicated pregnancies and neonates with critical conditions are often referred for specialized care. This highlights the importance of early antenatal risk stratification and reinforced peripartum care protocols.

Our results highlight several maternal and neonatal determinants of respiratory distress. The median maternal age was 35 years (Q1–Q3: 22–36). Advanced maternal age (30–40 years) is known to increase neonatal morbidity, partly due to chronic conditions such as hypertension and diabetes (2).

Birth weight was another determinant. The average was 3000 g (Q1–Q3: 2100–4050), with higher distress among neonates <2500 g. Over half (54.4%) were hypotrophic. Previous studies have shown intrauterine growth restriction, often linked to hypertension and reduced placental perfusion, predisposes to respiratory morbidity (3).

Regarding perinatal care, oxygen therapy was administered in all cases, yet 94.4% of neonates were not resuscitated at birth. Many were referred from peripheral centers with inadequate transport, illustrating systemic challenges. Similar to Alamneh et al (4), preventable factors such as preterm birth, low birth weight, prolonged labor, or meconium aspiration were frequent contributors.

Cesarean section was strongly linked to neonatal distress, in line with previous studies (5,6). The delayed

clearance of lung fluid and reduced catecholamine release in scheduled cesarean deliveries impair lung adaptation to extrauterine life.

We also confirmed the association between maternal diabetes and neonatal respiratory distress. Poorly controlled diabetes induces fetal hyperglycemia, oxidative stress, and impaired lung maturation (7). Likewise, hypertensive disorders, especially pre-eclampsia, increased complications and NICU admissions, as reported elsewhere (8).

Maternal anemia (OR = 18.1) and gestational diabetes (OR = 3.65) emerged as major determinants of NRD ;nutritional deficiencies, especially iron and folate, likely explain this association.These results are consistent with previous studies showing that maternal health substantially influences neonatal respiratory adaptation through mechanisms involving inflammation, hypoxia, and metabolic imbalance (9).

Prolonged premature rupture of membranes (>12h) and abnormal amniotic fluid were also strongly associated with NRD, reflecting the infectious and inflammatory burden on the fetus that increases pulmonary vulnerability. These findings align with evidence linking intra-amniotic infection and fetal distress to meconium aspiration and inflammatory lung injury (10)

Prematurity (OR = 2.45) remains a dominant risk factor, largely due to surfactant deficiency and structural lung immaturity, while cesarean delivery (OR = 4.23) was associated with higher NRD risk, likely because of the absence of thoracic compression and incomplete fluid clearance during delivery, as seen in transient tachypnea of the newborn. This emphasizes the importance of avoiding non-indicated cesarean sections before 39 weeks of gestation (11)

A low 1-minute Apgar score and the need for neonatal resuscitation were the strongest indicators of NRD, with resuscitation showing the highest odds ratio (OR = 30.95). While these factors may reflect severity rather than causality, they remain critical early warning signs that predict the need for intensive respiratory support, consistent with findings from other cohorts (12).

Beyond classical regression, the CART model provided novel insights by highlighting hierarchical and conditional risk profiles. Among preterm infants, a low Apgar score pushed the likelihood of NRD beyond 90%, while among term infants, cesarean delivery was the dominant determinant. Such non-linear and context-dependent interactions are difficult to capture with traditional models. Machine learning thus provided clinically intuitive, interpretable decision trees that may help anticipate NRD and support individualized monitoring (13).

The correlation heatmap based on Spearman coefficients provided a more nuanced perspective on the associations between neonatal respiratory distress (NRD) and its main clinical predictors. We showed moderate positive associations with resuscitation at birth ($\rho = 0.46$), abnormal amniotic fluid appearance ($\rho = 0.43$), and maternal anemia ($\rho = 0.38$). Other factors such as prematurity ($\rho = 0.26$) and cesarean delivery ($\rho = 0.18$) exhibited weaker associations, while gestational diabetes was negatively correlated with NRD ($\rho = –0.36$). This pattern emphasizes that NRD arises from a combination of interrelated factors rather than from uniformly strong predictors.

Clinically, the strongest correlations observed with resuscitation at birth and abnormal amniotic fluid underscore the importance of immediate perinatal assessment and management in predicting and preventing NRD. The negative association with gestational diabetes may reflect better antenatal monitoring and planned deliveries, potentially reducing the risk of neonatal complications.

The heatmap therefore complements classical inference, not by confirming universally strong correlations, but by highlighting the hierarchical and differential weight of predictors. This integrative approach strengthens interpretability and bridges classical epidemiological methods with AI-based models. In particular, it supports the careful selection of relevant variables for machine learning, avoiding overfitting while ensuring clinical plausibility.

Our findings align with broader literature advocating the use of AI and data mining tools in healthcare decision-making. Malak et al. emphasized that the complexity of NICU environments, characterized by heterogeneous real-time processes, cannot be fully addressed by a single tool and requires advanced data mining methods and multi-agent architectures (23). In line with this perspective, our study demonstrates that machine learning, particularly Random Forest, holds significant potential for improving NRD prediction and reducing neonatal complications (24).

Similarly, research on maternal and child health has highlighted the value of decision support systems that integrate systemic analysis and data mining algorithms across medical, social, and organizational dimensions. Such systems provide clinicians and policymakers with evidence-based insights to design targeted interventions (25). Taken together, these parallels underscore the growing relevance of AI in supporting effective strategies to reduce neonatal morbidity and mortality (26,27). Moreover, the NICU is particularly

well-suited for AI applications due to the large volume of high-dimensional data generated, including continuous monitoring, laboratory results, imaging, and medical records, which provide a robust foundation for training and validating AI algorithms (28).

Conclusion

This study identified key determinants of neonatal respiratory distress (NRD) through integrated classical and AI analyses. Resuscitation at birth, abnormal amniotic fluid, and maternal anemia were major predictors, while prematurity and cesarean delivery showed weaker links. The combined use of logistic regression and AI models enhances understanding and supports the development of neonatal risk-prediction tools, especially in limited-resource settings.

Strengths and Perspectives

Integrating machine learning with traditional statistics provided a clearer view of NRD determinants and uncovered interactions missed by classical models. Despite its retrospective, single-center design, this study highlights the potential of AI-based decision-support systems to improve perinatal risk stratification and neonatal care.

What is already known on this topic

Neonatal respiratory distress remains one of the leading causes of neonatal morbidity and mortality in low- and middle-income countries.

Classical statistical models, such as logistic regression, have been widely used to identify risk factors but often fail to capture complex, non-linear interactions between variables.

Machine learning methods, including decision trees, have been proposed in recent years to improve neonatal risk prediction but are rarely applied in African neonatal cohorts.

What this study adds

This study is the first in Morocco to integrate logistic regression and CART machine learning models for the analysis of neonatal respiratory distress.

The combined use of classical and AI-based approaches improved the interpretability of clinical predictors, highlighting maternal anemia, gestational diabetes, cesarean delivery, and prematurity as key risk factors.

The results provide an evidence-based framework for developing AI-assisted clinical decision tools in neonatal units in resource-limited settings.

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