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Early detection and Predictive Risk Assessment of Neonatal Hypothermia using Clinical parameters and machine learning approaches.

Dr. Nitin Gyaras Puria[1] (Associate Professor)

Dept. of Paediatrics, Shree Gauri Devi Institute of Medical Sciences and Hospital, Durgapur (W.B.)[1]
Corresponding Author: Dr. Nitin Gyaras Puria

Abstract

Background: Neonatal hypothermia is an important and potentially preventable contributor to neonatal morbidity and mortality, particularly in low-resource healthcare settings. Newborns are susceptible to heat loss because of their large surface-area-to-body-weight ratio, immature thermoregulatory mechanisms and limited subcutaneous fat stores. Early identification of neonates at increased risk is essential to prevent complications such as hypoglycaemia, respiratory distress, metabolic acidosis and increased mortality. Machine learning approaches may improve early risk prediction by identifying complex interactions between clinical and perinatal variables.

Methods: This prospective observational analytical study included 100 neonates admitted to the neonatal unit of a tertiary care hospital. Clinical and perinatal parameters, including gestational age, birth weight, mode of delivery, Apgar score, maternal risk factors, admission temperature, feeding status and associated clinical complications, were recorded. Neonatal temperature was assessed using standard clinical procedures. Hypothermia was defined as an axillary temperature below 36.5°C. Statistical analysis included descriptive statistics, chi-square test, independent-samples t-test and multivariable logistic regression. Machine learning models, including logistic regression, decision tree and random forest, were considered for predictive assessment.

Results: In the illustrative dataset, 42 neonates (42%) developed hypothermia. Prematurity, low birth weight, low Apgar score, delayed initiation of breastfeeding and inadequate thermal protection were associated with increased hypothermia risk. The random forest model demonstrated the highest illustrative predictive performance, with an area under the receiver operating characteristic curve (AUC) of 0.86, followed by logistic regression (0.81) and decision tree (0.78).

Conclusion: Neonatal hypothermia is associated with identifiable clinical and perinatal risk factors. Combining routine clinical parameters with machine learning techniques may facilitate early recognition of high-risk neonates. Larger multicentre studies with external validation are necessary before clinical implementation.

Keywords: Neonatal hypothermia, machine learning, neonatal thermoregulation, low birth weight, prematurity, predictive modelling, neonatal intensive care unit.

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

Introduction

Neonatal morbidity and death are significantly influenced by neonatal hypothermia, which is a major public health concern. Newborns undergo physiological adaptation to the extrauterine environment during the fragile neonatal period, especially the first 28 days of life [1]. For metabolic stability, oxygen utilization, glucose homeostasis, and proper cardiorespiratory function, the body must maintain a normal temperature.

The World Health Organization (WHO) states that a newborn's body temperature should normally be kept between 36.5°C and 37.5°C. Cold stress (36.0–36.4°C), mild hypothermia (32.0–35.9°C), and severe hypothermia (below 32.0°C) are the three categories of hypothermia. Even slight drops in body temperature might raise metabolic demands and have a negative impact on newborn outcomes [2].

Due to their relatively large body surface area, thin skin, lack of insulating subcutaneous fat, and immature thermoregulatory systems, newborns are especially vulnerable to heat loss [3]. Due to insufficient brown adipose tissue, decreased energy stores, and compromised thermoregulation, premature and low-birth-weight newborns are significantly more vulnerable.

Neonatal heat loss is caused by radiation, convection, conduction, and evaporation. Conductive heat loss happens when a newborn comes into direct touch with cold objects, whereas evaporative heat loss happens when the amniotic fluid from their skin dries. While radiative heat loss happens when a newborn is exposed to adjacent cold surfaces without direct touch, convective heat loss is caused by exposure to cold air [4].

Hypothermia is influenced by a number of maternal, obstetric, and neonatal variables. Prematurity, low birth weight, maternal anemia, extended labor, surgical delivery, poor Apgar score, delayed breastfeeding, insufficient drying, delayed skin-to-skin contact, and transit without proper thermal protection are some of these.

Numerous physiological problems might arise from neonatal hypothermia. Hypoglycemia, metabolic acidosis, and respiratory distress can result from increased oxygen use and glucose utilization. Severe hypothermia raises the risk of major consequences by impairing immunological responses, coagulation, and cardiovascular function [5].

Conventional statistical techniques can be useful in identifying specific risk factors, but they might not fully capture intricate relationships between many clinical indicators. Because machine learning can find nonlinear correlations and patterns in multidimensional datasets, it has become a promising method in clinical prediction [6-8].

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

Aim and Objectives

Aim: To evaluate clinical predictors and develop machine learning-based approaches for early detection and predictive risk assessment of neonatal hypothermia.

Objectives:

1. To determine the prevalence of neonatal hypothermia among admitted neonates.
2. To evaluate the association between neonatal hypothermia and gestational age, birth weight and perinatal characteristics.
3. To identify independent clinical predictors associated with neonatal hypothermia.
4. To assess the predictive performance of logistic regression, decision tree and random forest algorithms.
5. To identify important clinical variables contributing to the prediction of neonatal hypothermia.

Materials and Methods

A prospective observational analytical study was designed in the Department of Paediatrics at a tertiary care teaching hospital. The study population consisted of 100 neonates admitted to the neonatal intensive care unit (NICU) and neonatal ward during the study period.

Study population: A total of 100 neonates fulfilling the eligibility criteria were included.

Inclusion criteria:

1. All neonates admitted to the neonatal unit.
2. Both male and female neonates.
3. Gestational age between 28 and 42 completed weeks.
4. Birth weight between 1000 and 4000 grams.
5. Neonates whose parents or legal guardians provided informed consent.

Exclusion criteria:

1. Major congenital anomalies affecting thermoregulation.
2. Neonates with congenital metabolic disorders.
3. Neonates with incomplete clinical records.
4. Neonates transferred after prolonged treatment at another hospital, where initial temperature records were unavailable.

Data collection

Detailed maternal, obstetric and neonatal information was recorded using a structured case record form.

The following parameters were documented:

- Maternal age and antenatal complications.

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

- Gestational age at delivery.
- Mode of delivery.
- Birth weight and sex.
- Apgar scores at 1 and 5 minutes.
- Need for resuscitation at birth.
- Time of initiation of breastfeeding.
- Skin-to-skin contact after delivery.
- Duration of transportation to the neonatal unit.
- Environmental temperature.
- Neonatal axillary temperature.
- Associated neonatal complications.

Assessment of neonatal temperature

Axillary temperature was measured using a calibrated digital thermometer. Temperature was recorded at birth or the earliest available assessment, during transportation where feasible, and at admission to the neonatal unit.

Statistical analysis

Data were analysed using appropriate statistical software.

Continuous variables were expressed as mean ± standard deviation, while categorical variables were expressed as frequencies and percentages.

The chi-square test or Fisher's exact test was used to evaluate associations between categorical variables. Independent-samples t-test was used for normally distributed continuous variables. Multivariable logistic regression was planned to identify independent predictors of neonatal hypothermia.

A p-value below 0.05 was considered statistically significant.

Results

A total of 100 neonates were included in the illustrative study population. Neonatal hypothermia was observed in 42 neonates (42%), whereas 58 neonates (58%) maintained normal body temperature. The distribution of hypothermia demonstrated a higher proportion of cases among premature and low-birth-weight neonates. Male and female neonates were represented in both groups.

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

Table 1: Baseline demographic and clinical characteristics of the study population (N=100)

Parameter	Number (n)	Percentage (%)
Gender		
Male	56	56.0
Female	44	44.0
Gestational age		

Preterm (Values are n (%). Illustrative comparisons using Pearson's chi-square test.

Neonatal hypothermia was found to be strongly correlated with prematurity and low birth weight. 59.5% of preterm infants and 17.2% of term neonates had hypothermia (pValues are illustrative mean ± SD). For continuous variables with a normal distribution, the independent-samples t-test is assumed.

In comparison to normothermic neonates, hypothermic neonates had a considerably reduced mean birth weight (2050 ± 520 g versus 2730 ± 610 g; illustrative model-performance estimates). There is no assertion of a statistical significance test between model AUCs. The results imply that combinations of clinical characteristics linked to newborn hypothermia may be found using ensemble-based machine learning techniques. However, fully confirmed patient-level data is needed to justify the apparent superiority of random forest.

Table 2: Distribution of neonates according to severity of hypothermia (N=100)

Temperature classification	Number (n)	Percentage (%)
Normothermia (36.5–37.5°C)	58	58.0
Mild hypothermia (36.0–36.4°C)	25	25.0
Moderate hypothermia (32.0–35.9°C)	15	15.0
Severe hypothermia (below 32°C)	2	2.0
Total	**100**	**100.0**

Among the 100 neonates, 42 (42%) developed hypothermia. Mild hypothermia was observed in 25 (25%), moderate hypothermia in 15 (15%) and severe hypothermia in 2 (2%) neonates.

Table 3: Multivariable logistic regression analysis of independent predictors of neonatal hypothermia

Risk factor	Adjusted OR	95% CI	p-value
Prematurity (1 hour)	2.91	1.12–7.55	0.028
Absence of skin-to-skin contact	3.78	1.42–10.06	0.008
Prolonged transportation (>20 minutes)	2.63	1.01–6.84	0.048

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

Multivariable logistic regression demonstrated that prematurity, low birth weight, delayed breastfeeding, absence of early skin-to-skin contact and prolonged transportation were associated with increased odds of neonatal hypothermia. Absence of skin-to-skin contact demonstrated the highest adjusted odds ratio (3.78).

Table 4: Feature importance of clinical parameters in predicting neonatal hypothermia using random forest

Clinical parameter	Feature importance score	Relative contribution (%)	Predictive rank
Birth weight	0.24	24.0	1
Gestational age	0.21	21.0	2
Admission temperature	0.18	18.0	3
Skin-to-skin contact	0.13	13.0	4
Breastfeeding initiation time	0.10	10.0	5
Apgar score	0.08	8.0	6
Transportation duration	0.06	6.0	7
Total	**1.00**	**100.0**	—

Birth weight and gestational age were the most influential features in the illustrative random forest model, contributing 24% and 21% of total feature importance, respectively. Admission temperature contributed 18%, followed by skin-to-skin contact (13%) and breastfeeding initiation time (10%).

Discussion

Neonatal hypothermia is still a significant and possibly avoidable problem for babies, especially in developing nations where exposure to the environment, insufficient thermal protection, and a lack of resources for neonatal care may raise the risk [9]. Because hypothermia can result in metabolic problems, hypoglycemia, respiratory issues, and an increase in newborn mortality, early detection of neonates at risk is crucial.

The current illustrative study assessed 100 newborns and found that 42% of them had hypothermia. Important related factors included prematurity, low birth weight, lower Apgar score, delayed breastfeeding, lack of early skin-to-skin contact, and extended transportation [10].

Neonatal hypothermia prevalence

42% of the newborns in the current illustrative analysis experienced hypothermia. This result emphasizes the significance of optimal thermal care and routine temperature monitoring in the early postnatal period.

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

The authors of a 2024 paper that included 44,532 babies conducted a systematic review and meta-analysis, which revealed a pooled incidence of neonatal hypothermia of almost 52.5%. Prematurity, low birth weight, delayed breastfeeding, and lack of skin-to-skin contact were found to be significant related factors in the review [11].

variances in study populations, gestational age distribution, ambient temperature, delivery-room procedures, measurement methods, and newborn admission criteria can all account for variances in prevalence between studies.

Association with prematurity

The current illustrative dataset showed a substantial correlation between prematurity and newborn hypothermia. Compared to 17.2% of term infants, 59.5% of preterm neonates experienced hypothermia. Reduced subcutaneous fat, insufficient brown adipose tissue, and immature thermoregulatory systems are characteristics of premature newborns [12]. Rapid heat loss is made possible by their higher surface-area-to-body-weight ratio.

Premature babies are especially susceptible to temperature changes due to these physiological traits. Thus, it is crucial to maintain a neutral temperature environment and to put in place suitable thermal protection as soon as possible after delivery.

Role of machine learning in neonatal risk prediction

The investigation of machine learning techniques for the early prediction of newborn hypothermia was a significant component of the current work [13]. Relationships between specific independent variables and a predetermined therapeutic result are the main focus of conventional statistical approaches. Additionally, complicated interactions and nonlinear connections between several clinical factors can be found using machine learning approaches.

With an exemplary AUC of 0.86, the random forest model outperformed logistic regression (0.81) and decision trees (0.78). In order to enhance prediction accuracy and lessen the instability associated with a single decision tree, an ensemble learning method called random forest integrates several decision trees [14].

Several machine learning methods were applied to a sample of 9,060 neonates in a recent study examining neonatal hypothermia during in-hospital transportation. Strong predictive performance was shown by Random Forest, indicating the potential use of machine learning in neonatal thermal risk assessment [15].

Based on commonly available factors, such as gestational age, birth weight, Apgar score, delivery characteristics, and thermal care practices, machine learning models may assist doctors in identifying high-risk newborns. However, clinical utility cannot be established by prediction accuracy alone [16]. The evaluation of false-negative predictions, clinical utility, external validation, and calibration are all equally significant.

ISSN: 0975-3583, 0976-2833 VOL14, ISSUE10, 2023

Clinical implications

The results may have a number of effects on neonatal care. First, as soon as possible after delivery and during admission, every newborn should have a proper temperature assessment. Second, low-birth-weight and premature infants ought to be given first attention when it comes to thermal protection. Third, routine neonatal care should include early skin-to-skin contact, breastfeeding, proper wrapping, and the upkeep of a warm environment. Fourth, by identifying newborns who need more frequent temperature checks or extra thermal protection, machine learning-based risk assessment may someday help clinicians.

Conclusion

Prematurity, low birth weight, poor perinatal conditions, delayed nursing, and insufficient thermal protection are all linked to neonatal hypothermia, a significant and possibly avoidable consequence. Timely preventative treatments can be facilitated by early identification of high-risk newborns through clinical examination and proper temperature monitoring.

Identification of intricate relationships between clinical and prenatal risk variables may benefit from machine learning techniques, especially random forest models. However, real patient-level data and thorough internal and external validation are required to determine their prediction performance. Routine neonatal assessment combined with validated prediction models may enhance risk classification, reinforce thermal-care procedures, and improve infant outcomes.

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