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Machine Learning Approaches for Predicting Neurodevelopmental Disorder Risk Among Neonates with Perinatal Asphyxia: A Review

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Abstract

Perinatal asphyxia remains a leading contributor to neonatal mortality and morbidity in Nigeria, with survivors facing a substantially elevated risk of long-term neurodevelopmental impairment, including cerebral palsy, intellectual disability, and epilepsy. Early identification of at-risk neonates is essential for timely intervention, yet conventional clinical assessment tools are often insufficient for early, individualized risk stratification, particularly in low-resource settings. This review synthesizes current evidence on the burden and pathophysiology of perinatal asphyxia, its established link to neurodevelopmental disorders, and the growing application of machine learning (ML) techniques, notably logistic regression and random forest, in neonatal risk prediction. A structured review of empirical and grey literature indicates that, although ML has shown promise for disease prediction and risk stratification in broader paediatric and obstetric contexts, no existing study has developed or validated an ML-based model specifically for predicting neurodevelopmental disorder risk among Nigerian neonates with perinatal asphyxia. Most available Nigerian evidence is hospital-based, retrospective, and lacks a predictive or nationally representative dimension. This review proposes a conceptual machine learning pipeline, comprising data acquisition, preprocessing, feature engineering, model training, and evaluation, as a framework for addressing this gap. The findings underscore the potential of interpretable and ensemble-based ML models to support early clinical decision-making and improve neurodevelopmental outcomes in Nigeria and comparable low- and middle-income settings.

Keywords: Perinatal Asphyxia, Neurodevelopmental Disorders, Machine Learning, Random Forest, Logistic Regression, Neonatal Risk Prediction, Nigeria

1. Introduction

Nigeria continues to bear a disproportionately high burden of childhood mortality relative to global averages. According to the 2018 Nigeria Demographic and Health Survey, the infant mortality rate stood at 67 deaths per 1,000 live births, while the under-five mortality rate reached 132 deaths per 1,000 live births, implying that more than one in eight Nigerian children do not survive to their fifth birthday (Federal Ministry of Health [FMOH], 2022) [10]. Globally, an estimated 2.3 million neonates died within the first 28 days of life in 2022 alone, equivalent to roughly 6,500 deaths per day and accounting for approximately 47% of all under-five deaths (World Health Organization International, 2024) [29]. More recent national data from the 2023–2024 NDHS Key Indicators Report show a decline in under-five mortality to 102 per 1,000 live births; although this reflects modest progress, the figure remains far above the Sustainable Development Goal (SDG) target of 25 per 1,000 live births (Oweibia *et al*., 2025) [20].

Perinatal asphyxia is a principal driver of this mortality burden and is independently associated with substantial long-term morbidity, including motor and cognitive impairment among survivors (West & Briggs, 2024) [28]. The World Health Organization defines perinatal asphyxia as the failure of a newborn to initiate and sustain breathing at birth, arising from reduced blood supply and inadequate oxygen exchange to the brain and other vital organs during the perinatal period; the condition is estimated to affect approximately 6 in every 1,000 full-term live births worldwide (Alfaifi *et al*., 2025) [1]. Beyond its acute mortality risk, perinatal asphyxia is a potentially preventable cause of cerebral injury, with long-term sequelae that include cerebral palsy, intellectual disability, epilepsy, attention-deficit/hyperactivity disorder, autism spectrum disorder, and, in some reports, schizophrenia. Globally, an estimated one million children who survive birth asphyxia go on to experience permanent neurodevelopmental impairment (Ansari *et al.*, 2023) [3]. Neurodevelopmental disorders (NDs) as a group affect more than 10% of the global population and impose considerable lifelong functional and economic costs (Toki *et al.*, 2024) [26].

In Nigeria, an estimated 274,000 neonatal deaths occurred in 2022, approximately one-third of which were attributable to birth asphyxia; reported hospital prevalence ranges from 3% to 30% across regions, and in-hospital case fatality has been reported as high as 31.1% (West & Briggs, 2024) [28]. Survivors are at risk of further mortality from complications such as aspiration and systemic infection, and of long-term sequelae including cerebral palsy, cognitive and psychomotor impairment, seizures, blindness, and hearing loss (Gillam-Krakauer *et al.*, 2025) [11]. Clinically, neonatal status following suspected asphyxia is assessed through umbilical cord blood pH and the Apgar scoring system; a cord pH below 7.0 is strongly suggestive of asphyxia, while Apgar scores of 7–10, 4–6, and 0–3 correspond respectively to normal status, moderate compromise, and severe asphyxia (Kinoshita *et al.*, 2025) [15]. Because early recognition materially improves outcomes, there is a clear clinical rationale for tools capable of flagging at-risk neonates earlier and more precisely than conventional scoring permits.

Advances in machine learning (ML) offer a computational avenue for addressing this need. ML algorithms are able to model complex, high-dimensional clinical datasets and extract informative patterns that are difficult to discern through conventional statistical approaches, providing a basis for more accurate and efficient diagnostic and risk-prediction systems (Toki *et al.*, 2024) [26]. This review therefore examines the current evidence on the burden and mechanisms of perinatal asphyxia, its relationship to neurodevelopmental disorders, and the application of machine learning, specifically logistic regression and random forest, to neonatal and developmental risk prediction, with a view to identifying the gap that a Nigeria-focused predictive model would need to address.

The review is guided by the aim of examining how machine learning can be applied to predict neurodevelopmental disorder risk among neonates with perinatal asphyxia in Nigeria, pursued through three objectives: (i) reviewing existing literature on the application of machine learning to the prediction of neurodevelopmental disorders; (ii) outlining a machine learning modelling approach suited to predicting neurodevelopmental disorder risk in neonates; and (iii) identifying the quantitative metrics (accuracy, precision, recall, and F1-score) appropriate for evaluating such models. Early identification of infants at risk of neurodevelopmental impairment is of particular importance, since interventions delivered during the critical window of early brain development and heightened neuroplasticity are associated with improved long-term outcomes (Manzini *et al.*, 2024) [17]. By consolidating this evidence, the review provides a starting point for the development of predictive tools capable of supporting timely clinical decision-making for at-risk neonates in Nigeria and comparable low-resource settings.

2. Materials and Methods

2.1 Review Approach and Literature Search Strategy

This review adopts a narrative, structured approach to literature synthesis, combined with the outline of a conceptual machine learning framework derived from methodological patterns identified in the reviewed literature. Relevant literature was identified through searches of PubMed, Scopus, Google Scholar, and institutional or governmental repositories, including reports of the Nigeria Demographic and Health Survey (NDHS), the Federal Ministry of Health (FMOH), and the World Health Organization (WHO). Search terms combined variations of "perinatal asphyxia", "birth asphyxia", "neurodevelopmental disorder", "neonatal outcome", "machine learning", "predictive modelling", "logistic regression", and "random forest", conjoined with "Nigeria" or "sub-Saharan Africa" where applicable.

Studies and reports published between 2018 and 2026 were prioritized to capture recent epidemiological trends and methodological developments, although foundational conceptual and theoretical sources published earlier were retained where they remained substantively relevant. Eligible sources included peer-reviewed journal articles, systematic reviews, national survey reports, and clinical or public-health guidance addressing the epidemiology, clinical assessment, pathophysiology, or neurodevelopmental sequelae of perinatal asphyxia, or the application of machine learning to neonatal, paediatric, or developmental risk prediction. Sources not available in English, or without clear relevance to perinatal asphyxia, neurodevelopmental outcomes, or predictive modelling, were excluded. Retrieved sources were screened for relevance, and findings were extracted and organized thematically into: (i) the epidemiology and clinical features of perinatal asphyxia; (ii) the pathophysiological link between perinatal asphyxia and neurodevelopmental disorders; (iii) the theoretical grounding for the review; and (iv) the application of machine learning techniques to related prediction problems, summarised in a structured empirical review table.

2.2 Conceptual Framework for Machine Learning-Based ND Risk Prediction

To translate the reviewed evidence into an applicable framework, this review further outlines a conceptual machine learning pipeline for neurodevelopmental disorder (ND) risk prediction, framed as a binary classification problem in which the target variable denotes the presence or absence of ND risk in neonates with a history of perinatal asphyxia. This framework, synthesized from the methodological approaches reported across the reviewed studies, is intended as a template for future empirical application rather than as a report of new primary data collection.

Candidate data sources identified from the review, suited to studying perinatal asphyxia and neurodevelopmental risk in the Nigerian context, are summarised in Table 1. These include nationally representative survey data (NDHS), routine facility-based and WHO-collaborative datasets, and relevant open-access clinical datasets used in comparable published studies.

Table 1: Candidate Data Sources for ND Risk Prediction Modelling

Dataset	Source / Custodian	Key Variables	Records	Access
NDHS 2018 / 2024	DHS Program / FMOH Nigeria	Birth history, neonatal outcomes, ANC visits, delivery mode, maternal age	~40,000 households	Free (registration)
MPD-4-QED	WHO / FMOH Nigeria	Birth asphyxia incidence, Apgar score, cord pH, NICU admission, mortality	67,602 babies	WHO collaboration
UCI CTG Dataset	UCI Machine Learning Repository	FHR, uterine contractions, Apgar score, umbilical pH, fetal state classification	2,126 records	Freely available
Iran Neuro-Dev Dataset (2024)	Mashhad University of Medical Sciences	Bayley Scales (cognitive, language, motor), maternal factors, NICU data	Published open dataset	Free (Elsevier)

Table 2: Structured Overview of Study Variables

Variable Type	Variable Name	Description / Measurement	Scale
Dependent (target)	ND Risk	Binary outcome: 0 = No Risk, 1 = At Risk of neurodevelopmental disorder	Nominal
Independent	Apgar Score (1 min / 5 min)	Neonatal assessment score at 1 and 5 minutes after birth (0–10)	Ordinal
Independent	Gestational Age	Duration of pregnancy at delivery, in completed weeks	Continuous
Independent	Birth Weight	Weight of neonate at birth, in kilograms	Continuous
Independent	Mode of Delivery	Vaginal, caesarean section, or instrumental delivery	Nominal
Independent	Cord Blood pH	Umbilical arterial pH measured within the first hour of life	Continuous
Independent	Maternal Age	Age of the mother at time of delivery, in years	Continuous
Independent	Antenatal Visits	Number of antenatal care visits attended during pregnancy	Discrete
Independent	Maternal Hypertension	Presence of hypertension during pregnancy (0 = No, 1 = Yes)	Nominal
Independent	Maternal Diabetes	Presence of diabetes mellitus during pregnancy (0 = No, 1 = Yes)	Nominal
Independent	Resuscitation Required	Whether neonatal resuscitation was required at birth (0 = No, 1 = Yes)	Nominal
Independent	NICU Admission	Whether the neonate was admitted to the neonatal intensive care unit (0 = No, 1 = Yes)	Nominal
Independent	Seizures	Occurrence of neonatal seizures (0 = No, 1 = Yes)	Nominal

2.3 Variables and Data Preprocessing

Table 2 summarizes the categories of variables relevant to modelling ND risk following perinatal asphyxia, comprising a binary target variable (ND risk: at risk / not at risk, operationalized using clinically validated thresholds such as Apgar score, hypoxic-ischaemic encephalopathy diagnosis, or developmental delay flags) and a set of predictor variables spanning neonatal, obstetric, and maternal domains.

Prior to model development, candidate datasets would require preprocessing to ensure quality and analytical suitability. Data cleaning would involve median imputation for missing continuous variables and mode imputation for missing categorical variables, with missing variables exceeding 30% evaluated for exclusion, alongside removal of duplicate records to reduce redundancy and data leakage. Categorical variables would be encoded according to their structure: binary variables (e.g., presence of maternal hypertension) via label encoding; unordered nominal variables with more than two categories (e.g., mode of delivery) via one-hot encoding; and ordinal variables (e.g., Apgar score categories) via order-preserving encoding.

Two supervised ML algorithms are proposed within this framework: logistic regression, serving as an interpretable baseline that models the log-odds of ND risk and yields directly interpretable coefficients suited to clinical communication; and random forest, an ensemble method that aggregates the predictions of multiple decision trees trained on bootstrapped samples and feature subsets, offering improved capacity to capture non-linear relationships and feature interactions within high-dimensional clinical data. Model performance would be evaluated using four standard classification metrics derived from the confusion matrix: accuracy (the proportion of correctly classified instances among all instances), precision (the proportion of predicted positive cases that are true positives), recall (the proportion of actual positive cases correctly identified), and the F1-score (the harmonic mean of precision and recall, useful under class imbalance).

3. Results and Discussion

3.1 Definition, Causes, and Clinical Assessment of Perinatal Asphyxia

Birth asphyxia, as defined by the WHO, refers to the failure of a neonate to initiate and maintain breathing at birth and is estimated to be responsible for approximately 900,000 deaths annually. The condition reflects a broader spectrum of pathophysiological events characterized by reduced oxygen supply and impaired circulation to vital organs during the perinatal period; when severe or sustained, the resulting hypoxic injury affects the brain first and may extend to the lungs, heart, and kidneys (Healthline, 2023).

The reviewed literature identifies birth asphyxia as multifactorial, arising from maternal or fetal factors before delivery, during labour, or across both periods, with reduced cerebral blood flow as the common underlying mechanism regardless of the precipitating cause (Techane *et al.*, 2022) [25]. Reported risk factors include advanced maternal age (≥35 years) and low educational attainment; maternal conditions such as diabetes, hypertension, anaemia, and intrahepatic cholestasis; delivery-related factors, particularly mode of delivery; and fetal or obstetric factors including multiple gestation, labour anaesthesia, abnormal presentation, preterm birth, low birth weight, and abnormalities of the cord, placenta, or amniotic fluid (Su *et al.*, 2024) [24]. Survivors may recover without disability or develop multi-organ complications requiring specialized follow-up, hypoxic-ischaemic encephalopathy (HIE) is among the most significant of these complications and is strongly associated with cerebral palsy, seizure disorders, sensory impairment, and deficits in language and social functioning (Njinkui *et al.*, 2023) [19]. Globally, neonatal conditions remain a leading cause of under-five mortality, with preterm birth complications (17.8%) and intrapartum-related events (11.6%) ranking among the principal contributors, and intrapartum complications alone accounting for an estimated 42 million disability-adjusted life years (Kawakami *et al*., 2021) [14].

There is no universal consensus on diagnostic criteria for perinatal asphyxia, although guidelines from the American College of Obstetricians and Gynecologists and the American Academy of Pediatrics emphasize umbilical cord blood pH, Apgar score, and neurological signs (Ribeiro *et al*., 2023) [23]. Clinically, perinatal asphyxia is commonly defined by the presence of at least one of the following: an Apgar score of ≤5 at 10 minutes, resuscitation exceeding 10 minutes, or metabolic acidosis indicated by umbilical arterial pH ≤7.0 or base excess ≤ −12 mmol/L within the first hour of life (Ikechebelu *et al*., 2024) [13].

3.2 Global and Nigerian Burden

In 2022, an estimated 2.3 million children died during the neonatal period globally, roughly 6,500 deaths per day, representing 47% of all under-five mortality; perinatal asphyxia is estimated to contribute approximately 24% of neonatal deaths worldwide and is a major cause of long-term neurodevelopmental impairment, including cerebral palsy, developmental delay, and cognitive dysfunction (Welay *et al*., 2026; World Health Organization International, 2024) [27, 29]. Nigeria bears a substantial share of this burden, an estimated 270,000 neonatal deaths occurred in 2019, but deficiencies in the country's vital statistics system limit accurate estimation of prevalence and risk factors, with most available evidence derived from retrospective or localised hospital studies (Alfaifi *et al*., 2025; Ikechebelu *et al*., 2024) [1, 13]. This gap in nationally representative data constrains evidence-based service planning and, by extension, the development of predictive tools calibrated to the Nigerian population.

3.3 Neurodevelopmental Disorders and Their Link to Perinatal Asphyxia

Childhood disability is a substantial global public-health concern: an estimated 1.3 million newborns survive each year with major disabilities, and a further one million experience long-term moderate or mild impairment, including learning and behavioural difficulties. In low- and middle-income countries, nearly 80% of childhood disability is attributed to perinatal brain injury, with neonatal encephalopathy the most prevalent cause (Manzini *et al*., 2024) [17]. Neurodevelopmental disorders (NDs) affect over 10% of the global population and encompass autism spectrum disorder, attention-deficit/hyperactivity disorder, intellectual disability, specific learning disorder, and communication disorders, each with distinct but overlapping functional consequences (Toki *et al*., 2024) [26].

Mechanistically, perinatal asphyxia disrupts oxygen exchange between mother and fetus, commonly through uteroplacental insufficiency, cord prolapse, or placental abruption. Acute asphyxia typically presents with observable fetal distress, while chronic hypoxia triggers compensatory redistribution of blood flow to the brain, heart, and adrenal glands, an adaptive but ultimately unsustainable response whose failure leads to cumulative metabolic and structural brain injury (Mota-Rojas *et al*., 2022) [18]. The severity and duration of hypoxic insult determine the pattern of injury, acute severe asphyxia affecting deep grey-matter structures, and prolonged partial hypoxia affecting the cortex and white matter, both patterns being strongly linked to later cerebral palsy, epilepsy, cognitive impairment, and behavioural disorders. Neonates with HIE are at markedly increased risk of long-term impairment, with severity of HIE correlating with degree of disability (Manzini *et al*., 2024) [17], and longitudinal evidence indicates persistent deficits in motor function, language, and cognition into later childhood. Collectively, this evidence underscores the value of early identification and risk stratification, particularly in low-resource settings where advanced diagnostic tools such as fMRI or cranial ultrasound are frequently unavailable.

3.4 Theoretical Framework

This review situates the problem of ND risk prediction within the Biopsychosocial Model, originally proposed by George Engel, which holds that health outcomes emerge from the dynamic interaction of biological, psychological, and social factors (Bolton, 2023; Lugg, 2021) [8, 16]. Applied here, biological factors correspond to hypoxic-ischaemic brain injury from perinatal asphyxia, while psychological and social determinants, such as the caregiving environment, healthcare access, and availability of early intervention, shape developmental trajectories (Bolton, 2023; Hunt, 2022) [8, 12]. This is complemented by Neuroplasticity Theory, which emphasizes the brain's capacity for structural and functional reorganization in response to experience, particularly during early developmental stages, and underscores why early detection and intervention are disproportionately beneficial during periods of heightened plasticity (Pickersgill *et al*., 2022; Been *et al*., 2022) [21, 4]. Together, these frameworks justify a predictive, early-intervention-oriented approach: the Biopsychosocial Model accounts for the multifactorial origins of ND risk, while Neuroplasticity Theory provides the rationale for why early, ML-supported identification can materially alter outcomes.

3.5 Machine Learning in Healthcare and Neonatal Risk Prediction

Machine learning (ML) enables algorithms to learn from data and generate predictions without explicit rule-based programming, with supervised learning particularly suited to clinical contexts where labelled outcome data are available. ML techniques can bridge population-level assessment and individualised evaluation, uncovering subtle developmental patterns in large, complex datasets that are difficult to detect through conventional methods (Benson *et al*., 2025) [5], and are increasingly viewed as a promising tool for diagnosis and outcome prediction given the volume and complexity of medical data (Darsareh *et al*., 2023) [9]. This capacity to model non-linear, high-dimensional relationships is particularly relevant to neurodevelopmental outcomes, which are inherently multifactorial (Toki *et al*., 2024) [26].

Logistic regression remains a foundational technique for binary classification in clinical prediction, estimating the conditional probability of an outcome through the logistic function and expressing predictor contributions as interpretable log-odds ratios, an important property in medical settings where transparency supports clinical trust. Its principal limitation is the assumption of linearity in the log-odds, which constrains its ability to capture complex interactions among predictors. Random forest, by contrast, is an ensemble method that builds multiple decision trees on bootstrapped subsets of data and features, aggregating their outputs by majority vote (classification) or averaging (regression); this reduces variance, improves robustness to overfitting, and provides feature-importance estimates via measures such as Gini impurity reduction (Yi *et al.*, 2025) [30]. Within the reviewed literature, these two algorithms recur as complementary choices, an interpretable baseline paired with a higher-capacity ensemble model, for clinical risk-prediction tasks.

3.6 Empirical Review of Related Work

Table 3 summarises key studies relevant to the epidemiology of perinatal asphyxia, neurodevelopmental outcomes, and machine learning applications in related domains, together with gaps identified in each.

Table 3: Empirical Review of Related Studies

Author (Year)	Study Focus	Key Findings	Identified Gap(s)
FMOH (2022) [10]	National maternal and child health outcomes in Nigeria; SDG alignment and UHC policy	Infant mortality of 67/1,000 and under-five mortality of 132/1,000 live births reported; Nigeria pursuing SDGs via UHC	Limited focus on specific conditions such as perinatal asphyxia and its neurodevelopmental sequelae
WHO International (2024) [29]	Global neonatal mortality estimates; asphyxia as contributor to under-five deaths	~2.3 million neonatal deaths globally in 2022; asphyxia contributes ~24% of neonatal deaths	Global aggregates obscure country-specific burden; limited predictive-modelling guidance
Oweibia *et al.* (2025) [20]	NDHS 2023–2024 under-five mortality trends	Under-five mortality declined to 102/1,000, still above SDG target of 25/1,000	No ML or predictive component; regional disparities under-explored
West & Briggs (2024) [28]	Birth asphyxia-related mortality and morbidity in Nigeria	274,000 neonatal deaths in 2022 (~1/3 asphyxia-related); in-hospital mortality up to 31.1%	Retrospective design; no ML-based prediction model; outcomes not tracked post-discharge
Alfaifi *et al.* (2025) [1]	Global prevalence/risk factors of perinatal asphyxia in LMICs	Asphyxia affects ~6/1,000 full-term births; key maternal/fetal risk factors identified	Limited Nigeria-specific applicability; predictive modelling not explored
Ansari *et al.* (2023) [3]	Long-term neurodevelopmental consequences of asphyxia globally	~1 million survivors develop permanent impairment; links to ADHD, ASD, schizophrenia	No computational or ML-based framework proposed
Toki *et al.* (2024) [26]	ML for neurodevelopmental disorder detection	NDs affect >10% globally; supervised ML shows promise for early detection	Not specific to perinatal asphyxia; lacks LMIC/African validation
Manzini *et al.* (2024) [17]	Early identification of neurodevelopmental impairment in LMICs	Neonatal encephalopathy is leading preventable cause; advanced diagnostics often unavailable	No ML model proposed; limited focus on routinely available variables
Mota-Rojas *et al.* (2022) [18]	Pathophysiology of perinatal asphyxia	Details mechanisms of hypoxic injury and the 'diving reflex'	No clinical prediction component; largely derived from experimental models
Ikechebelu *et al.* (2024) [13]	Clinical diagnosis and prevalence in Nigeria	Prevalence 3–30% across regions; diagnostic criteria outlined	No predictive modelling; retrospective records introduce selection bias
Njinkui *et al.* (2023) [19]	Neurodevelopmental outcomes following HIE	HIE severity correlates with degree of disability	No ML methods applied; limited generalisability to Nigeria
Benson *et al.* (2025) [5]	ML bridging population- and individual-level developmental assessment	ML uncovers subtle developmental patterns undetectable by conventional methods	No Nigeria-specific or asphyxia-focused application
Yi *et al.* (2025) [30]	Random forest in clinical prediction	RF improves accuracy/robustness via ensemble bootstrapping	Not applied to asphyxia or ND outcomes in LMICs
Kawakami *et al.* (2021) [14]	Global burden of intrapartum-related neonatal mortality	Intrapartum events cause 11.6% of under-five deaths; 42 million DALYs	No Nigeria-specific or predictive framework
Reichard & Zimmer-Bensch (2021) [22]	Heterogeneity/mechanisms of NDs	NDs show complex, variable symptom profiles across biological/psychosocial domains	No ML-based classification; limited focus on perinatal origins or African contexts

3.7 Synthesis and Research Gap

Across the reviewed evidence, three consistent patterns emerge. First, the epidemiological burden of perinatal asphyxia and its neurodevelopmental sequelae in Nigeria is substantial but poorly characterized at a national level, with most available data derived from retrospective, hospital-based, or geographically localized studies (West & Briggs, 2024; Ikechebelu *et al.*, 2024) [28, 13]. Second, machine learning has demonstrated clear value in related domains, including cardiotocography-based asphyxia prediction (Kinoshita *et al.*, 2025; Ribeiro *et al.*, 2023) [15, 23], general child-development assessment (Benson *et al.*, 2025) [5], and broader neurodevelopmental disorder detection (Toki *et al.*, 2024) [26], and logistic regression and random forest recur as complementary, well-validated candidate algorithms for such tasks (Darsareh *et al.*, 2023; Yi *et al.*, 2025) [9, 30]. Third, and most critically, no identified study has combined these two threads: applying and comparing interpretable and ensemble ML models specifically to predict neurodevelopmental disorder risk among Nigerian neonates with perinatal asphyxia using nationally relevant data. Existing Nigerian and comparable sub-Saharan African studies are largely descriptive or hospital-based and do not incorporate predictive modelling components (Njinkui *et al.*, 2023; Manzini *et al.*, 2024) [19, 17], while ML-focused studies of NDs or asphyxia are rarely validated in Nigerian or other low-resource, nationally representative contexts (Toki *et al.*, 2024; Reichard & Zimmer-Bensch, 2021) [26, 22]. This review's proposed conceptual framework, spanning data acquisition, preprocessing, feature engineering, model training, and evaluation using accuracy, precision, recall, and F1-score, directly addresses this gap by outlining a pathway for developing and comparing logistic regression and random forest models for ND risk prediction using data relevant to the Nigerian setting.

4. Conclusion

Perinatal asphyxia remains a major, and largely preventable, contributor to neonatal mortality and long-term neurodevelopmental impairment in Nigeria, yet routine clinical tools such as the Apgar score and cord blood pH, while valuable, offer limited capacity for early, individualized risk stratification. This review has synthesized evidence on the epidemiology, pathophysiology, and clinical assessment of perinatal asphyxia, its established link to neurodevelopmental disorders, and the demonstrated but fragmented application of machine learning to related prediction problems. The evidence indicates that logistic regression and random forest are well-validated, complementary candidates for neonatal risk prediction, offering, respectively, interpretability and enhanced capacity to model non-linear clinical relationships. However, no existing study has applied these techniques specifically to predict neurodevelopmental disorder risk among Nigerian neonates with perinatal asphyxia using nationally relevant data. The conceptual machine learning pipeline outlined in this review, spanning data acquisition, preprocessing, feature engineering, model development, and standardized evaluation, offers a structured framework through which this gap can be addressed, with the ultimate aim of supporting earlier identification and more timely clinical decision-making for at-risk neonates.

5. References

1. Alfaifi J, Ahmed MA, Almutairi GS, Alhumaidi NH, *et al*. Global prevalence and risk factors of perinatal asphyxia: A review, 2025.
2. AlHabardi N, Adam I. Prevalence of perinatal asphyxia and its associated factors among live birth in Khartoum, Sudan: A hospital-based cross-sectional study. BMC Pediatrics. 2025; 25(1):150. Doi: https://doi.org/10.1186/s12887-025-05499-7
3. Ansari F, Manazir Ali S, Firdaus U, Noor N. Neurodevelopmental outcomes in newborns with birth asphyxia with special reference to hearing and visual impairment. International Journal of Contemporary Pediatrics. 2023; 10(8):1231-1235. Doi: https://doi.org/10.18203/2349-3291.ijcp20232240
4. Been LE, Sheppard PAS, Galea LAM, Glasper ER. Hormones and neuroplasticity: A lifetime of adaptive responses. Neuroscience & Biobehavioral Reviews. 2022; 132:679-690. Doi: https://doi.org/10.1016/j.neubiorev.2021.11.029
5. Benson FN, Chelangat D, Brink W, Mwangala PN, Waljee AK, Moyer CA, *et al*. Application of machine learning in early childhood development research: A scoping review. BMJ Open. 2025; 15(8):e100358. Doi: https://doi.org/10.1136/bmjopen-2025-100358
6. Biedroń N, Tokarzewska A, Rekowska A, Kwiatkowska A, Urbaś W, Tarkowska A. Neonatal asphyxia - predicting its occurrence and neurodevelopment of children after hypothermia treatment in the context of machine learning models - literature review. Journal of Pre-Clinical and Clinical Research. 2024; 1(18):26-32. Doi: https://doi.org/10.26444/jpccr/183436
7. Birth Asphyxia: Causes, Treatment, and Outlook. Healthline, June 5, 2023. https://www.healthline.com/health/birth-asphyxia
8. Bolton D. A revitalized biopsychosocial model: Core theory, research paradigms, and clinical implications. Psychological Medicine. 2023; 53(16):7504-7511. Doi: https://doi.org/10.1017/S0033291723002660
9. Darsareh F, Ranjbar A, Farashah MV, Mehrnoush V, Shekari M, Jahromi MS. Application of machine learning to identify risk factors of birth asphyxia. BMC Pregnancy and Childbirth. 2023; 23(1):156. Doi: https://doi.org/10.1186/s12884-023-05486-9
10. Federal Ministry of Health [FMOH]. National maternal, newborn and child health statistics report, 2022.
11. Gillam-Krakauer M, Shah M, Gowen Jr CW. Birth Asphyxia. In StatPearls. StatPearls Publishing, 2025. http://www.ncbi.nlm.nih.gov/books/NBK430782/
12. Hunt J. Holistic or harmful? Examining socio-structural factors in the biopsychosocial model of chronic illness and disability. Disability & Society, 2022. 37(6):1032-1061. Doi: https://doi.org/10.1080/09687599.2022.2099250
13. Ikechebelu JI, Eleje GU, Onubogu CU, Ojiegbe NO, Ekwochi U, Ezebialu IU, *et al*. Incidence, predictors and immediate neonatal outcomes of birth asphyxia in Nigeria. BJOG: An International Journal of Obstetrics & Gynaecology. 2024; 131(S3):88-100. Doi: https://doi.org/10.1111/1471-0528.17816
14. Kawakami MD, Sanudo A, Teixeira MLP, Andreoni S, De Castro JQX, Waldvogel B, *et al*. Neonatal mortality associated with perinatal asphyxia: A population-based study in a middle-income country. BMC Pregnancy and Childbirth. 2021; 21(1):169. Doi: https://doi.org/10.1186/s12884-021-03652-5
15. Kinoshita H, Fukunishi H, Shibata C, Hirakawa T, Miyata K, Yotsumoto F. Neonatal asphyxia prediction using features extracted from cardiotocography data by explainable artificial intelligence. Informatics in Medicine Unlocked. 2025; 54:101636. Doi: https://doi.org/10.1016/j.imu.2025.101636
16. Lugg W. The biopsychosocial model: History, controversy and Engel. Australasian Psychiatry. 2021; 30(1):129-136. Doi: https://doi.org/10.1177/10398562211037333
17. Manzini E, Borellini M, Belardi P, Mlawa E, Kadinde E, Mwibuka C, *et al*. Factors associated with mortality and neurodevelopmental impairment at 12 months in asphyxiated newborns: A retrospective cohort study in rural Tanzania from January 2019 to June 2022. BMC Pregnancy and Childbirth. 2024; 24(1):660. Doi: https://doi.org/10.1186/s12884-024-06837-w
18. Mota-Rojas D, Villanueva-García D, Solimano A, Muns R, Ibarra-Ríos D, Mota-Reyes A. Pathophysiology of Perinatal Asphyxia in Humans and Animal Models. Biomedicines. 2022; 10(2):347. Doi: https://doi.org/10.3390/biomedicines10020347
19. Njinkui DN, Enyama D, Fokam YD, Mewolo DLN, Kana CAN, Njonnou SRS, *et al*. Neurodevelopmental Outcome of Newborns Aged More than 34 Weeks Gestational Age Managed for Birth Asphyxia in Douala (Cameroon): A Single Hospital-Based Study. Open Journal of Pediatrics. 2023; 13(6):838-851. Doi: https://doi.org/10.4236/ojped.2023.136092
20. Oweibia M, Elemuwa CO, Egberipou T, Timighe GC,

Sylvanus P, Wilson TR. Maternal and child health trends in Nigeria: A scoping review of NDHS 2018 vs. NDHS 2023, 2025.

21. Pickersgill JW, Turco CV, Ramdeo K, Rehsi RS, Foglia SD, Nelson AJ. The combined influences of exercise, diet and sleep on neuroplasticity. Frontiers in Psychology. 2022; 13:831819. Doi: https://doi.org/10.3389/fpsyg.2022.831819
22. Reichard J, Zimmer-Bensch G. The Epigenome in Neurodevelopmental Disorders. Frontiers in Neuroscience. 2021; 15:776809. Doi: https://doi.org/10.3389/fnins.2021.776809
23. Ribeiro M, Nunes I, Castro L, Costa-Santos C, Henriques TS. Machine learning models based on clinical indices and cardiotocographic features for discriminating asphyxia fetuses-Porto retrospective intrapartum study. Frontiers in Public Health. 2023; 11:1099263. Doi: https://doi.org/10.3389/fpubh.2023.1099263
24. Su Y-J, Liu W, Xing R, Yu Z, Peng Y, Luo W. Prevalence and risk factors associated with birth asphyxia among neonates delivered in China: A systematic review and meta-analysis. BMC Pediatrics. 2024; 24(1):845. Doi: https://doi.org/10.1186/s12887-024-05316-7
25. Techane MA, Alemu TG, Wubneh CA, Belay GM, Tamir TT, Muhye AB, *et al*. The effect of gestational age, low birth weight and parity on birth asphyxia among neonates in sub-Saharan Africa: Systematic review and meta-analysis: 2021. Italian Journal of Pediatrics. 2022; 48(1):114. Doi: https://doi.org/10.1186/s13052-022-01307-5
26. Toki EI, Tsoulos IG, Santamato V, Pange J. Machine Learning for Predicting Neurodevelopmental Disorders in Children. Applied Sciences. 2024; 14(2):837. Doi: https://doi.org/10.3390/app14020837
27. Welay GY, Gezae KE, Nesredin A, Abebe HT, Berhe A, Gebre YG, *et al*. Predicting birth asphyxia in newborns via supervised machine learning: A prospective cohort study in Tigray, Ethiopia 2025. In Review, 2026. Doi: https://doi.org/10.21203/rs.3.rs-8460279/v1
28. West BA, Briggs D. Prevalence, Complications, Outcomes and Associated Factors of Perinatal Asphyxia in a Neonatal Unit in Port Harcourt, Southern Nigeria. The Nigerian Health Journal. 2024; 24(4):1809-1821. Doi: https://doi.org/10.60787/TNHJ.V24I4.935
29. World Health Organization International. Newborn mortality [Fact sheet]. WHO, March 14, 2024. https://www.who.int/news-room/fact-sheets/detail/newborn-mortality
30. Yi S, Li Q, Shi X, Teng Y, Xu X. Construction and validation of neonatal asphyxia risk prediction model based on machine learning. In Review, 2025. Doi: https://doi.org/10.21203/rs.3.rs-7660175/v1