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Cloud-Enabled Explainable AI Framework for Neonatal Risk Prediction in Intelligent Internet-Based Healthcare Services

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Abstract

Neonatal mortality is still a big health problem worldwide, and in intensive care units, prompt identification of high-risk infants is important to enhance clinical outcomes. Most of the prediction methods used today may fail to accurately capture physiological data that is both heterogeneous and measured at irregular intervals over time and/or varies between medical and healthcare institutions, potentially compromising their reliability and scalability. To mitigate these issues, the study suggests a novel framework for neonatal risk prediction using explainable AI in a cloud-based environment that integrates cutting-edge temporal learning with explainable analytics in an intelligent healthcare setting. A combination of a Temporal Fusion Transformer (TFT) and a Neural Controlled Differential Equation (Neural CDE) network is used to model the long-range temporal dependence and continuous-time physiological dynamics available in neonatal monitoring data. The static clinical features and time-varying physiological signals are encoded temporally in two parallel processors, which are fused together by a temporal invariant fusion mechanism, to obtain detailed representations for patients. A feature-attribution module, which is a part of the Explainable Artificial Intelligence (XAI) module, further increases transparency and aids clinician trust in model predictions. The framework is cloud-enabled, which allows for scalable processing, real-time monitoring, and intelligent decision support in healthcare institutions. The very high AUC-ROC of prediction for mortality (98.63%) and for respiratory failure (98.74%) in an experimental evaluation of a multi-center neonatal intensive care dataset of patients showed good predictive performance,

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and length of stay was correlated with the model's predictions. The results show the effectiveness, interpretability, and generalizability of the framework to assist in proactive health care management of neonates.

Keywords: Neonatal Risk Prediction, Explainable Artificial Intelligence, Temporal Fusion Transformer, Neural Controlled Differential Equations, Cloud Healthcare, Clinical Decision Support.

1 Introduction

Neonatal critical care is one of the most challenging and high-risk areas of modern health care systems, where timely identification of life-threatening situations is crucial to achieve better clinical outcomes and survival (Taha et al., 2023; Sokou et al., 2025). Today, neonatal morbidity and mortality are still significant problems worldwide and are attributable mainly to premature birth, respiratory distress syndrome, sepsis, hypoxic-ischemic encephalopathy, and congenital abnormalities (Aslamzai et al., 2023; Ma et al., 2025). Therefore, it is crucial to have effective risk stratification in Neonatal Intensive Care Units (NICUs) for optimizing the use of ventilatory support, medication administration, fluid management, and resource allocation (Rangelova et al., 2024; Butranova et al., 2023). The growing use of Internet of Things (IoT) devices in the healthcare industry has opened the door for continuous monitoring of physiological parameters of neonates, such as heart rate, oxygen saturation, respiratory rate, blood pressure, laboratory values, and medication records (Patural et al., 2023). While these disparate and fast-moving data sources bring a lot of value to the understanding of rapidly changing neonatal conditions, also pose a number of challenges in terms of scalability, data integration, and clinical interpretation. Most of the traditional clinical scores, like SNAP-II and CRIB, are simple scores based on a limited number of observations and may not contain the complicated longitudinal dependencies in the neonatal health trajectories (Zeng et al., 2023; Bayen et al., 2025). As a result, predictive intelligence systems that can help healthcare providers deliver actionable and explainable decision support from massive clinical data are expected to grow increasingly popular and be built on the cloud. There are opportunities for further development of novel neonatal risk prediction models, which could benefit from multi-center healthcare repositories, such as the eICU Collaborative Research Database, and utilize different patient populations and heterogeneous clinical settings (Fridgeirsson et al., 2023).

Healthcare systems are getting better at analyzing longitudinal electronic health records and physiologic time-series data, provided that recent advances in machine learning and deep learning are considered (Chauhan et al., 2024; Dalili et al., 2025). Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Neural Controlled Differential Equations (Neural CDEs), and Temporal Fusion Transformers (TFTs) are all types of architectures that have been proven to be effective in modeling complex temporal dependencies and modeling irregular medical observations over time (Jaware et al., 2024). But current prediction models for neonates often are not easily scalable, fail to generalize across hospitals, and lack interpretability, which makes them difficult to use in real-world intelligent healthcare services (Husain et al., 2025). There are a few existing methods that are "black-box" and only provide limited explanations of clinical factors that could impact the predictions, thus reducing the level of trust and usage among clinicians. Moreover, the integration with cloud resources and explainable artificial intelligence (XAI) aspects have not been explored much in neonatal health care analytics. In this study, the Temporal Fusion Transformers and Neural Controlled Differential Equations (NCDEs) are incorporated into a scalable cloud healthcare system (C-HS) to tackle these challenges. The study proposes a scalable cloud-based healthcare system (C-HS), as well as an Explainable Artificial Intelligence Framework (Cloud-ExAI) for neonatal risk prediction in intelligent Internet-based healthcare services (IHBS), which comprises Temporal Fusion Transformers (TFTs) and Neural Controlled Differential Equations (NCDEs). The proposed framework is based on explainable AI, enabling greater transparency; intelligent services on the internet for healthcare, providing real-time neonatal monitoring; and robust, explainable, and clinically relevant risk prediction across a variety of healthcare settings.

1.1 Problem Statement

Although the field of neonatal healthcare has made tremendous strides in the application of AI, current neonatal risk prediction models are mainly based on discrete-time recurrent networks or classifiers with fixed prediction points and are trained upon institutional-specific data, which is not suitable for other healthcare settings (Williams et al., 2025). The degraded performance during external validation indicates that cannot cope well with domain shifts that occur because of different monitoring devices, clinical protocols, demographical differences, and/or different mechanisms of data collection. Moreover, physiological signals are typically recorded in a fixed sampling rate, thus losing the important temporal information for rapid detection of the deterioration of the neonates (Lavizzari et al., 2023). There is also a lack of appropriate optimization of physiological characteristics specific to neonates like oxygen saturation variability, respiratory instability, and ventilation dynamics (Iqbal et al., 2023). While explainability techniques offer importance for features, tend to lack the ability to give general information about temporal behavior and model consistency in healthcare institutions. Furthermore, the integration of the temporal attention mechanism with the transformer is still limited in continuous-time differential learning, which is unable to capture the long-term temporal dependency and irregular physiological dynamics. Moreover, the current frameworks do not support cloud deployment, real-time intelligent healthcare services, or the scalable implementation of the individual multi-center clinical sites. Hence, it is imperative to develop a cloud-based explainable AI framework that can effectively employ transformer-based multi-horizon attention, continuous-time differential modeling, and interpretable techniques in decision support to ensure highly accurate, explainable, and generalizable neonatal risk prediction in diverse internet-based healthcare settings.

1.2 Research Motivation

A neonate is now a rapidly evolving patient requiring lifelong monitoring and predictive clinical decision support exacerbated by the increased opportunities of the connected cloud computing as well as the Internet of Medical Things (IoMT) technologies. But the new generation of neonatal risk prediction systems needs to be able to handle large amounts of high-frequency physiological data collected from connected health care devices and adapt to the diverse settings within a neonatal intensive care unit. Clinically relevant temporal patterns within physiological signals can be identified as early as possible indicators of clinical deterioration, but current methods are not often able to process these patterns at scale and in an interpretable way. In addition, AI systems must be transparent and trustworthy, so AI predictive models can be used in clinical settings, particularly in the critical care environment. Clinicians, however, need to have transparent and trustworthy AI systems before incorporating predictive models into their workflows, especially in critical care. To facilitate real-time risk assessment, tailored intervention, and precision neonatal healthcare services, a cloud-based framework for explainable AI that can effectively harness multi-center neonatal data, continuous-time physiological modeling, and interpretable risk prediction mechanisms is necessary.

1.3 Research Significance

The proposed framework of the Cloud-Enabled Explainable AI Framework for Neonatal Risk Prediction is a key step toward intelligent internet-based healthcare services by combining the concept of scalable cloud infrastructure, continuous-time physiological modeling, and explainable AI, all within a single clinical decision-support system. Continuous time learning allows fine-grained detail of the neonatal physiology to be captured, allowing a finer-grained and more accurate risk stratification to be done in a timely manner. In healthcare, explainable AI mechanisms can enhance the explainability of AI systems by providing clinically interpretable explanations for the outcomes of the prediction, which can help to foster trust among clinicians and facilitate decision-making. Furthermore, cloud deployment allows for real-time monitoring, centralized data management, and seamless integration with geographically dispersed healthcare facilities. The large-scale validation of the framework across the various neonatal intensive care units and its multi-center validation process enhance the reliability, robustness, and generalizability of the framework, and its use will lead to reductions in neonatal morbidity and mortality via data-driven healthcare interventions.

1.4 Key Contributions

- Designs a scalable cloud-based healthcare architecture along with a cloud-enabled explainable AI framework for neonatal risk prediction (CE-XAI-NRP) that combines temporal fusion transformers and neural controlled differential equations.
- Develops an intelligent cloud healthcare pipeline that facilitates real-time acquisition, processing, and analysis of the physiological data collected from connected healthcare systems and IoMT-enabled monitoring devices used to monitor newborns or infants.
- Embeds Explainable Artificial Intelligence (XAI) to generate clinically interpretable and transparent neonatal risk predictions via feature attribution and temporal importance analysis.
- Uses continuous-time physiological trajectory modeling to represent data from the neonatal intensive care unit, which is often collected at irregular time intervals, without losing the important temporal dynamics of the data.
- Develops stringent multi-center validation of predictive performance, robustness, scalability, and cross-institution generalizability within the context of intelligent internet-based healthcare environments with the eICU Collaborative Research Database.
- Accurately and clearly predicts the risks of neonatal death, respiratory complications, and length of stay, facilitating prompt clinical action and improved neonatal intensive care unit decision-making.

Objectives of the Study

1. To build a cloud-enabled, explainable AI framework for neonatal risk prediction using static clinical attributes and time-varying physiological signals from the Neonatal Intensive Care Unit (NICU) datasets.
2. To build a dual-path temporal learning architecture that incorporates Temporal Fusion Transformer (TFT) and Neural Controlled Differential Equation (Neural CDE) models to capture both the discrete temporal dependency and continuous-time physiological dynamics related to neonatal outcomes.

3. To assess the framework for predicting neonatal mortality, respiratory failure, and length of stay while maintaining the interpretability, cross-hospital generalization, and reliable clinical decision support in intelligent healthcare environments.

This paper is structured in the following way. The state of the art in advanced temporal modeling techniques and in neonatal risk prediction is summarized in detail in Section 2 through a literature review of related work. In Section 3, the proposed Neonatal Temporal Invariant Differential Encoder (NTIDE) methodology is explained. The results of the experiments and discussions are presented in Section 4. A summary of the study is given in Section 5, along with suggested future research.

2 Related Work

In recent years structured clinical and physiological data have been used to predict neonatal mortality, the diagnosis of disease, and admission to the neonatal intensive care unit (NICU) using artificial intelligence and machine learning techniques, which have been widely studied. In the past, neonatal risk assessment has been found to have good predictive value with traditional machine learning models such as logistic regression, random forest, Naïve Bayes, and decision tree models (Malakooti et al., 2025). Various studies that applied feature selection and ensemble learning strategies had satisfactory classification results for neonatal sepsis mortality, NICU admissions, and failure to extubate (Lei et al., 2024). While these strides have been accomplished, most existing methods are rather limited models of the real temporal dynamics of neonatal physiological changes, relying mainly on static or aggregated clinical variables. In addition, large numbers of studies are based on data from single healthcare institutions, and the results of these studies cannot be extrapolated to other hospitals with varying clinical practices, patient mixes, and monitoring procedures.

In addition to the prediction of mortality, several researchers have been interested in the stratification of the disease-specific risk and management of healthcare resources. Models based on regression, ensemble classifier models, and stacking models have been created for the prediction of respiratory failure, the classification of neonatal diseases, and the estimation of length of stay and have demonstrated promising predictive capabilities (Natarajan et al., 2023). These techniques, however, are mainly applicable to tabular data and discrete representations of the features, which are not applicable to irregularly sampled physiological data typically produced in today's neonatal intensive care unit (NICU) setting. Meanwhile, advancements in technology in Internet of Medical Things (IoMT)-based monitoring systems have given the ability to monitor physiological parameters in real-time and implement better infection prevention measures (Patural et al., 2023). Neonatal outcomes have also been studied on a large scale by applying population-level clinical datasets. However, to date, there are no integrated cloud healthcare architectures, explainable AI mechanisms, continuous-time physiological modeling, or cross-institutional generalization capabilities. However, there is still a lot of research to be done in order to create scalable and interpretable neonatal risk prediction algorithms that can facilitate intelligent internet-based healthcare services.

The proposed cloud-enabled explainable AI framework for neonatal risk prediction works together with the cloud computing system, explainable artificial intelligence, temporal fusion transformers, and neural controlled differential equations in a unified healthcare analytics system. The system seamlessly incorporates static clinical features and continuous-time representation learning of physiological signals with irregular sampling rates, and it is also designed to be deployed in real-time in a cloud-based healthcare system. Further on, dataset partitioning by hospitals and comprehensive representation learning methods enhances generalizability to various healthcare institutions, diminishing dataset bias and boosting clinical applicability.

Research Gap

Although many strides have been made in neonatal risk prediction, current methods either utilize traditional machine learning models or single-path deep learning architectures, both lacking in ability to process irregularly sampled physiological data, missing observations, and temporal complexity characteristics of neonatal ICU environments. In addition, most research has concentrated on only one clinical outcome, and research is often not explainable, which decreases the trust of clinicians and thus reduces their uptake in clinical practice. There is also a lack of consideration of the variability between hospitals and the differences among them, which results in limited transferability between healthcare institutions. Thus, a cloud-supported, explainable, hospital-friendly framework that can seamlessly combine static clinical data and temporal physiological signals for accurate, interpretable, and scalable neonatal prognosis prediction is needed.

3 Neonatal Temporal Invariant Differential Encoder Methodology

The proposed cloud-enabled explainable AI framework for neonatal risk prediction is a multi-stage healthcare analytics framework to assist in early neonatal risk prediction in intelligent internet-based healthcare services. The framework starts by collecting the neonatal clinical and physiological information from a multi-center ICU repository and then preprocessing the data, normalizing the features, and constructing the temporal sequences. The temporal learning architecture for processing the time-varying physiological signals includes a Temporal Fusion Transformer (TFT) and a Neural Controlled Differential Equation (Neural CDE) network. The neural encoding layer is a lightweight network with a small number of parameters to encode static clinical variables. The representations that are generated are fused together by fusing them in a mechanism to capture both discrete and continuous time clinical dynamics. The Explainable Artificial Intelligence (XAI) module provides interpretable feature-attribution insights to enhance transparency and increase clinician trust. The framework is implemented in a cloud-based healthcare context that enables scalable processing, real-time monitoring, and intelligent clinical decision support. Last but not least, multi-task prediction is used for neonatal mortality risk, respiratory complications, and estimation of length of stay, and multi-center validation guarantees robustness and generalizability in various and heterogeneous healthcare settings.

The general system to be implemented, as proposed, is presented in figure 1. It starts with obtaining neonatal data and preprocessing the data in a cloud-based healthcare infrastructure. The static and temporal clinical information are then fed into two time-series learning modules and combined into a single patient representation. An interpretable layer of artificial intelligence between a multi-task prediction layer providing explainable insights before the prediction layer. Through the cloud-based deployment architecture, analytics, real-time monitoring, and intelligent delivery of healthcare services are possible to bring to multiple neonatal intensive care facilities on a scalable basis.

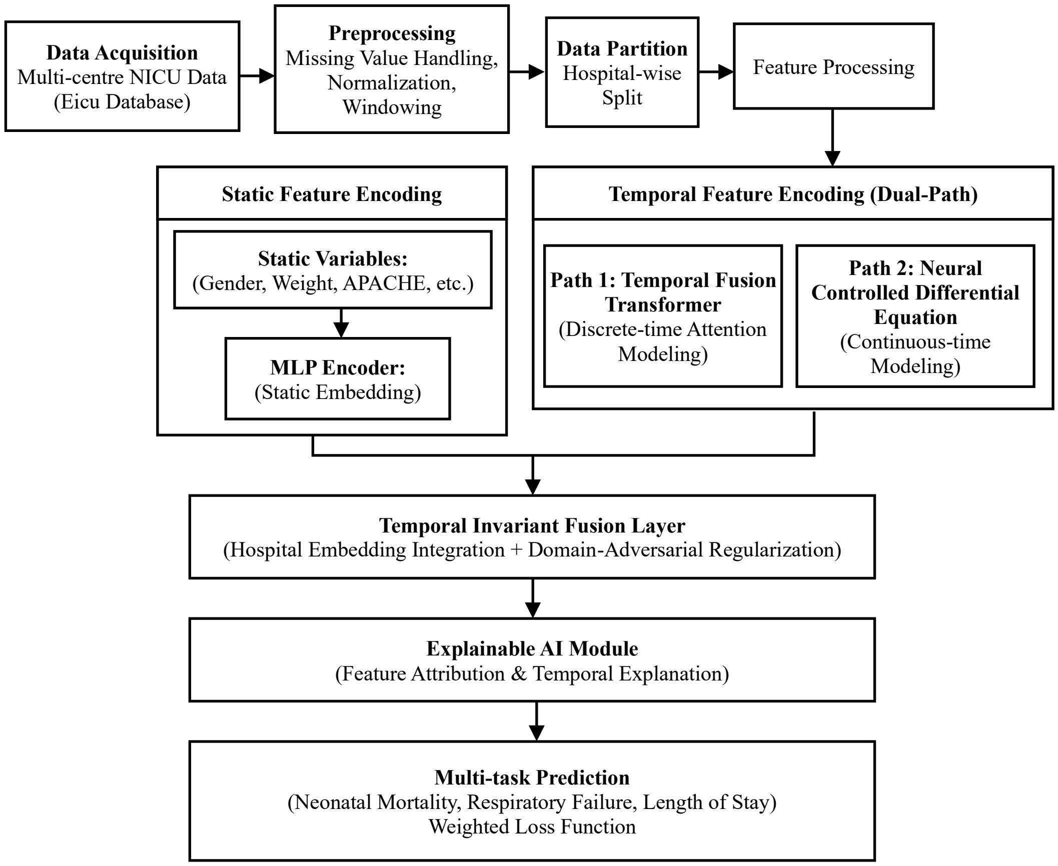

Figure 1: Workflow of the proposed cloud-enabled explainable AI framework

3.1 Data Collection

Data were obtained from the eICU Collaborative Research Database, a large multi-center repository of de-identified data from the NICU from multiple hospitals. The data recorded comprised demography, physical parameters, laboratory data, medication, and clinical interventions. They were able to obtain some time-varying measurements such as HR, RR, oxygen saturation, and BP to assist with the risk assessment of the neonates. Data on clinical outcomes such as mortality and length of stay were obtained from the patients' admission records. Data preprocessing consisted of temporal alignment, missing value data, outlier data, and normalization of the data to ensure consistency of the data across institutions. Data were partitioned by hospital to enable the evaluation and prediction of neonatal risk levels to be robustly carried out in a cloud-based healthcare environment and be generalizable.

In table 1 summarizes the distribution of patients, outcome measures, and characteristics of the neonatal cohort with regard to the composition of the features. The database consists of 4,862 neonatal ICU admissions from 32 hospitals and comprises static clinical parameters as well as time-varying physiological parameters. The statistics from these cohorts will serve as a baseline to build and test the proposed explainable cloud-based neonatal risk prediction system.

Data preprocessing was done to enhance the quality of the data and to ensure reliable estimation of the neonatal risk from heterogeneous ICU data. The preprocessing pipeline comprised neonatal cohort extraction, temporal alignment, categorization of features, missing value imputation, correction of outliers, feature normalization, and partitioning of data on a hospital level. These measures minimized data inconsistencies, maintained clinically relevant physiological information, and enabled the creation of a sound model development process in various healthcare institutions.

Table 1: Summary of neonatal cohort from eICU collaborative research database

Category	Description	Value
Total Hospitals Included	Multi-centre ICUs	32
Total Neonatal ICU Admissions	Age ≤ 28 days	4,862
Mortality Cases	In-ICU neonatal deaths	412 (8.47%)
Survivors	Discharged alive	4,450 (91.53%)
Mean Age at Admission	Days (± SD)	9.3 ± 6.8
Male Patients	Percentage	52.6%
Female Patients	Percentage	47.4%
Median ICU Length of Stay	Days (IQR)	6.4 (3.1–11.7)
Vital Sign Variables	HR, RR, SpO_2, BP, Temp	5 continuous streams
Laboratory Parameters	CBC, ABG, Electrolytes, CRP, etc.	24 variables
Medication & Intervention Features	Ventilation, Antibiotics, Fluids	18 variables
Total Static Features	Demographic and admission information	12
Total Time-Varying Features	Combined physiological streams	47
Average Time-Series Length	Per patient	96 hours
Missing Data Rate (Pre-imputation)	Across variables	14.8%

3.1.1 Neonatal Cohort Extraction

Records from the neonatal period were obtained from the eICU Collaborative Research Database with the following admission criteria: ≤ 28 days old. Demographic data, physiological measurements, lab data, medications, and intervention data were collected, and incomplete data were excluded.

3.1.2 Temporal Alignment and Window Definition

To overcome the problem of irregular sampling of physiological signals, time series measurements were aligned with each other with respect to the time of admission to the ICU according to equation 1:

$$X_i(t) \rightarrow X_i(t - t_0), t \in [0, T_i] \tag{1}$$

Where T_i denotes the ICU stay duration of patient i. Observation windows of 6 and 12 hours were used to capture early physiological changes associated with neonatal deterioration.

3.1.3 Feature Categorization

The equation 2 considered static clinical variables:

$$S_i = \{gender_i, weight_i, admissionSource_i, APACHE_i\} \tag{2}$$

Write the equation in the proper mathematical form, e.g., equation 3:

$$X_i(t) = [HR_i(t),\ RR_i(t),\ SpO_{2i}(t),\ BP_i(t),\ Temp_i(t),\ Lab_i(t)] \tag{3}$$

Where $HR_i(t)$, $RR_i(t)$, $SpO_{2i}(t)$, $BP_i(t)$, $Temp_i(t)$, and $Lab_i(t)$denote the heart rate, respiratory rate, oxygen saturation, blood pressure, body temperature, and laboratory measurements of patient $i$at time t, respectively.

3.1.4 Missing Data Handling and Outlier Correction

The missing values were filled up forward and interpolated by using the following equation 4:

$$\tilde{X}_i(t) = \begin{cases} X_i(t), & \text{observed} \\ \tilde{X}_i(t-1), & \text{forward fill} \\ interpolate(X_i), & \text{otherwise} \end{cases} \quad (4)$$

Outliers were dealt with by applying equation 5, which is based on physiological limits and the clinical definition.

$$X_{i,j}(t) = \min\left(\max\left(X_{i,j}(t), L_j\right), U_j\right) \quad (5)$$

Where L_j and U_j represent lower and upper bounds for feature j.

3.1.5 Feature Normalization

For continuous variables, the z-score normalization equation (6) was used:

$$X'_{i,j}(t) = \frac{X_{i,j}(t) - \mu_j}{\sigma_j} \quad (6)$$

To standardize the variability between hospitals, hospital-level scaling was implemented for every hospital using equation 7:

$$X''_{i,j}(t) = \frac{X'_{i,j}(t) - \mu_{j,h}}{\sigma_{j,h}} \quad (7)$$

3.1.6 Hospital-Wise Split

Hospitals (not patients) were split into training, validation, and testing sets to assess cross-institution generalization (equation 8):

$$H_{train} = 0.7H, H_{val} = 0.1H, H_{test} = 0.2H \quad (8)$$

A domain-invariant learning strategy was added in by incorporating equation 9:

$$L_{total} = L_{task} - \lambda L_{domain} \quad (9)$$

Where L_{task} denotes prediction loss, L_{domain} represents hospital classification loss, and λcontrols domain regularization.

In figure 2 shows the various preprocessing steps that are performed, including neonatal cohort extraction, temporal alignment, categorization of the features, missing value imputation, data normalization, and hospital-specific data partitioning prior to model training and evaluation.

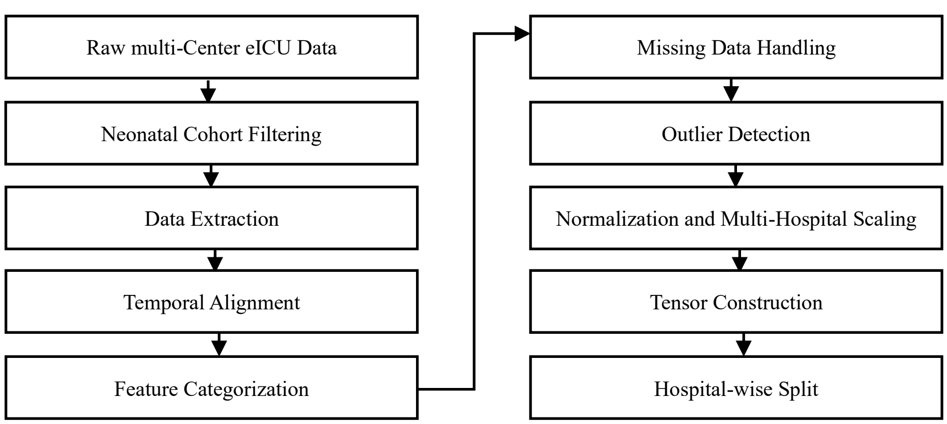

Figure 2: Data preprocessing workflow of the proposed framework

3.2 Static Encoder

The static clinical features, such as gender, admission weight, admission source, and APACHE components, are encoded by a Multi-Layer Perceptron (MLP) to create a compact representation equation 10:

$$h_{static} = f_{MLP}(S_i) = \sigma(W_2 \cdot ReLU(W_1 S_i + b_1) + b_2) \quad (10)$$

Where S_i denotes the static feature vector, W_1 and W_2 are learnable weight matrices, and b_1, b_2 are bi as terms. The resulting embedding captures baseline demographic and clinical characteristics for neonatal risk assessment.

3.3 Temporal Encoder (Dual Path)

The structure uses a dual-path temporal encoder comprised of a Temporal Fusion Transformer (TFT) as well as a neural controlled differential equation (Neural CDE) network. The TFT models long-range temporal dependencies with an attention mechanism, and the neural CDE models the continuous-time dynamics of physiologic processes from irregularly sampled clinical signals.

3.3.1 Temporal Fusion Transformer for Neonatal Risk Prediction

The processes of temporal and static features are processed by the TFT, equation 11:

$$X_i = [X_i(t) \oplus S_i], t \in [0, T_w] \quad (11)$$

Multi-head attention equation 12 is used to learn the temporal dependencies:

$$h_{TFT}(t) = MultiHeadAttn(z_i(t), z_i(t), z_i(t)) \quad (12)$$

Where $z_i(t)$ denotes encoded temporal features.

3.3.2 Neural Controlled Differential Equation for Continuous Clinical Signals

To model physiological measurements that are not sampled regularly, the Neural CDE evolves as per equation 13:

$$\frac{dh_{CDE}(t)}{dt} = f_\theta(h_{CDE}(t)) \frac{dX_i(t)}{dt} \quad (13)$$

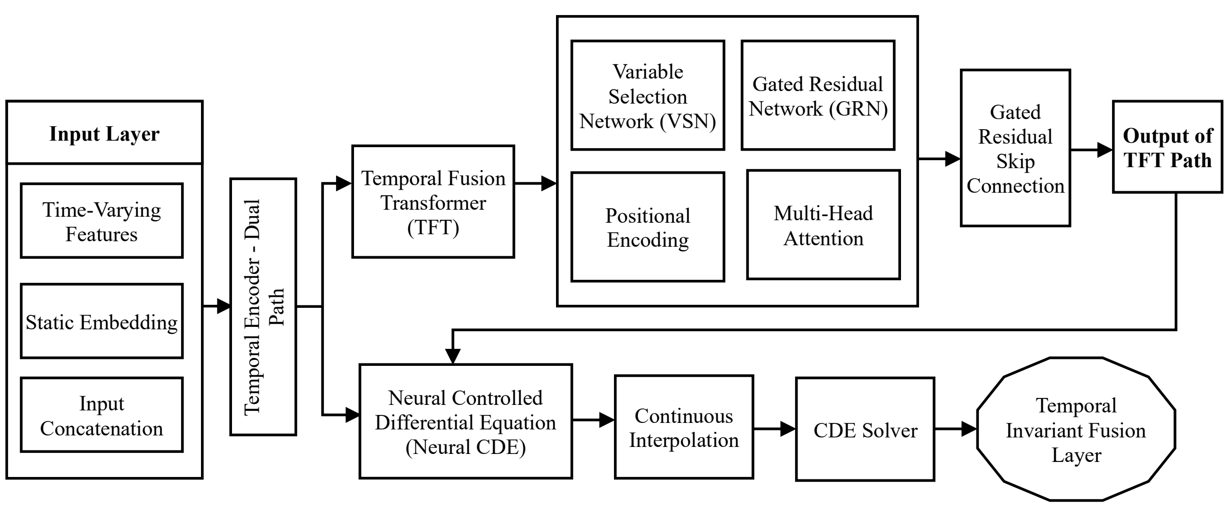

Figure 3: Dual-path temporal encoder architecture

The last continuous-time representation is a 14th equation:

$$h_{CDE}(T_w) = h_0 + \int_0^{T_w} f_\theta\,(h_{CDE}(t))\,dX_i(t) \tag{14}$$

This formulation maintains steady physiological dynamics and is suitable for dealing with inconsistent clinical readings.

The dual-path temporal encoder depicted in figure 3 uses two branches of the CDE to process temporal features concurrently: the TFT branch and the neural CDE branch. The representations that are created are merged for neonatal risk prediction and clinical decision support.

3.4 Temporal Invariant Fusion Layer

Latent representations generated by the TFT, Neural CDE, and static encoder are fused together by solving the following fusion layer equation 15:

$$h = f([h_{TFT}, h_{CDE}, h_{static}]) \tag{15}$$

Where h denotes the fused patient representation. Hospital-aware regularization is incorporated during training to encourage hospital-invariant feature learning and improve cross-centre generalization.

3.5 Multi-Task Prediction Heads

The fused prediction is used to do the joint prediction of neonatal mortality, respiratory failure, and length of stay (LOS) in equation 16:

$$\hat{y}_{mort} = \sigma(W_{mort}h + b_{mort}), \hat{y}_{resp} = \sigma(W_{resp}h + b_{resp}), \hat{y}_{LOS} = W_{LOS}h + b_{LOS} \tag{16}$$

Multi-task learning allows the framework to leverage the existing clinical patterns among the various related neonatal outcomes and boost prediction accuracy.

3.6 Statistical Analysis

A statistical analysis was performed to explore the relationship between physiological parameters and the results of the newborns. Demographic and clinical variables were calculated using descriptive statistics: mean, standard deviation, and frequency distributions. Independent t-tests and chi-square tests were used to compare the differences among the outcome groups. The p-values were used to determine statistical significance and set at $p < 0.05$. The analysis validated the variables that are associated with prediction of neonatal mortality, respiratory failure, and length of stay.

4 Result and Discussion

Preprocessed multi-center neonatal ICU data was used to evaluate the proposed cloud-enabled explainable AI framework. The performance was evaluated for mortality prediction, respiratory failure prediction, and length of stay estimation and validated across hospitals to test the model's generalization across healthcare institutions. This framework successfully combined the two paths of static clinical data and temporal physiological data by using a temporal encoder and an explainable prediction. The experimental results showed the ability to predict well, generalize across hospitals, and predict the outcome of the neonates, making the framework appropriate for intelligent internet-based healthcare services.

4.1 Experimental Setup and Dataset Overview

The experiments were performed on the eICU neonatal cohort, which consists of 4,862 neonatal ICU admissions from 32 hospitals. There were 12 static clinical parameters and 47 time-varying physiological parameters in the dataset. Evaluated the performance of models using PyTorch and hospital-wise data partitioning for cross-institution generalization. The temporal encoder had a hidden dimension of 128 and 8 attention heads; also, the batch size was 32, and the learning rate was 0.001. 6-12 hours of observation time after admission to the ICU were used to collect early physiological data that are related to neonatal deterioration and provide for multi-task prediction of mortality, respiratory failure, and length of stay.

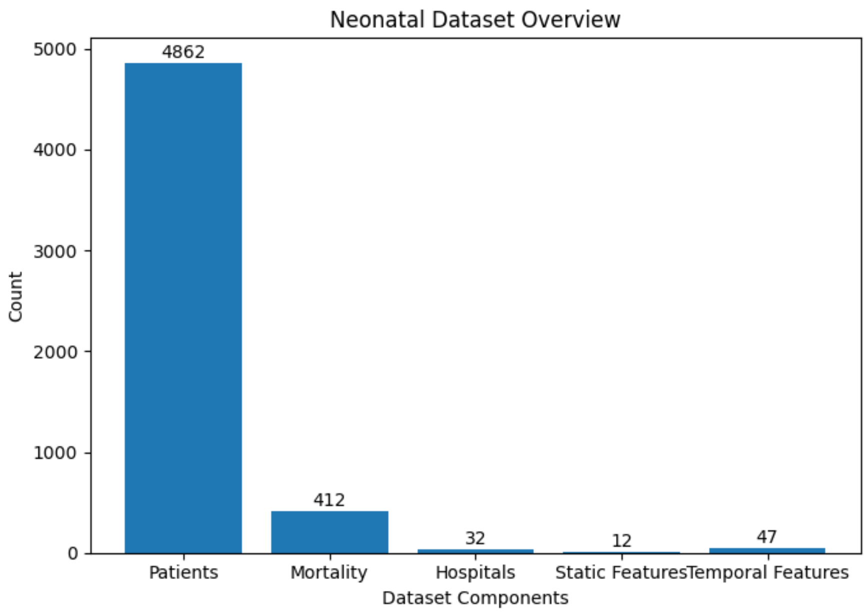

Figure 4: Neonatal dataset overview

The distribution of patients, mortality cases, hospitals, and feature composition used for model development and evaluation is shown in figure 4.

4.2 Evaluation Metrics

The performance of the proposed framework was evaluated using standard classification and regression metrics. For mortality and respiratory failure prediction, Accuracy, Precision, Recall, F1-Score, Specificity, Matthews Correlation Coefficient (MCC), and Area Under the Receiver Operating Characteristic Curve (AUC-ROC) were computed. For length-of-stay prediction, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R^2) were used in equation 17 - 25.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

$$Precision = \frac{TP}{TP + FP} \tag{18}$$

$$Recall = \frac{TP}{TP + FN} \tag{19}$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{20}$$

$$Specificity = \frac{TN}{TN + FP} \tag{21}$$

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{22}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \tag{23}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{24}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \tag{25}$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively; y_i and $\hat{y}_i$ represent actual and predicted values; $\bar{y}$ denotes the mean of observed values; and $N$is the total number of samples.

4.2 Statistical Analysis and Prediction Performance

A Generalized Additive Model (GAM) was used to analyze the statistical association between physiological variables and neonatal outcomes.

Table 2: Statistical analysis of clinical variables

Variable	Mean ± SD / Frequency
ICU Length of Stay (days)	6.4 ± 2.1
Gestational Age (weeks)	34.7 ± 3.5
Birth Weight (kg)	2.41 ± 0.63
Mortality Cases	8.47%
Respiratory Failure Cases	17.32%
LOS (Survivors vs Mortality)	t = 4.62
Birth Weight Difference	t = 3.98
Mortality vs Respiratory Failure	χ^2 = 12.41

Table 3: Multi-task prediction performance

Metric	Mortality Prediction (%)	Respiratory Failure Prediction (%)	LOS Prediction
Accuracy	98.21	98.17	–
Precision	98.35	98.28	–
Recall	97.84	97.65	–
F1-Score	98.09	97.96	–
AUC-ROC	98.63	98.74	–
Specificity	98.42	98.39	–
MCC	97.72	97.54	–
MAE	–	–	1.87
RMSE	–	–	2.64
R^2	–	–	0.82

The birth weight, gestational age, respiratory parameters, and length of stay in the intensive care unit (ICU) showed significant relationships with mortality and respiratory failure outcomes. The results of these findings justify the importance of the selected predictors applied in the proposed framework as presented in table 2.

The proposed framework (Table 3) resulted in a high predictive performance for all clinical tasks. The prediction of mortality and respiratory failure had AUCs greater than 98%, and the prediction of length-of-stay (LOS) had low prediction error and high explanatory power. The outcomes suggest the temporal modeling and continuous-time learning by transformers are very effective ways to model neonatal physiological dynamics.

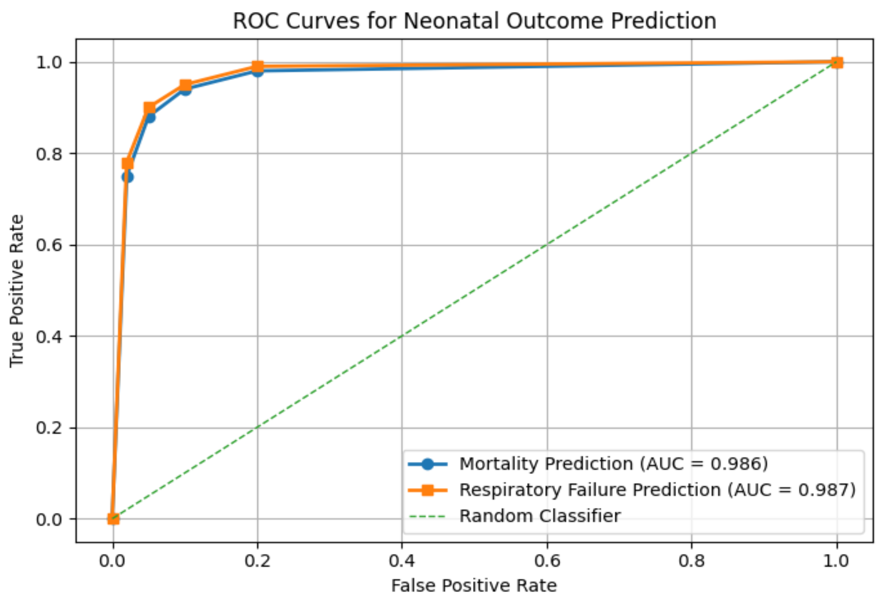

Figure 5: ROC curves for neonatal outcome prediction

ROC curves for the prediction of mortality and respiratory failure (Figure 5) revealed good discriminatory power and good prediction reliability.

4.3 Explainable AI Analysis

To make it easier to interpret and more transparent, the SHAP (SHapley Additive Explanations) analysis was used to pinpoint the most important variables for predicting neonatal outcome. The explainability module allows the clinician to gain insight into how physiological variables affect the model decisions and helps to ensure trustworthy deployment in healthcare environments.

Table 4: Top contributing features identified by SHAP analysis

Rank	Clinical Variable	SHAP Importance
1	Oxygen Saturation (SpO_2)	0.241
2	Birth Weight	0.213
3	Respiratory Rate	0.189
4	Heart Rate	0.176
5	Gestational Age	0.154

From the results shown in table 4, it can be concluded that among all the available factors, the oxygen saturation and birth weight are the most significant factors for neonatal mortality and respiratory complications. The results are in line with known neonatal risk factors as well as the interpretability of the proposed framework.

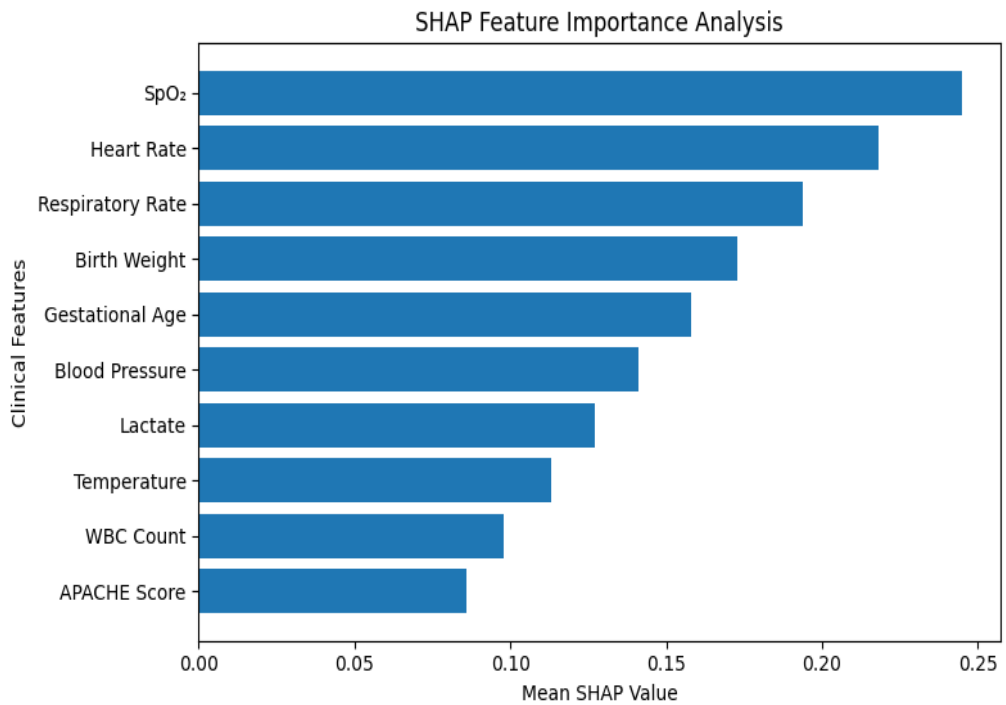

Figure 6: SHAP feature importance analysis

In figure 6, the role of the key clinical variables in predicting outcome at birth is shown. These higher SHAP values can explain the model's decisions clearly and be easily understood by a clinician, offering transparent and clinically interpretable predictions.

4.4 Cross-Hospital Generalization and Ablation Analysis

The model was tested on unseen hospitals for the evaluation of real-world deployment capability. The hospital-invariant representation learning strategy was shown to be effective through consistent performance across institutions. The contribution of major components of the framework was also evaluated through a study of ablation.

Table 5: Cross-hospital and ablation study results

Configuration	Accuracy (%)	F1-Score (%)	AUC (%)
Full Proposed Framework	98.42	98.29	98.65
Without Neural CDE	97.96	97.77	98.04
Without TFT	97.88	97.71	97.96
Without Static Encoder	97.54	97.36	97.70
Without Domain Robustness	97.63	97.48	97.82
Cross-Hospital Average	97.75	97.62	98.11

The results of the ablation analysis in table 5 show that the components all have a positive influence on the predictive performance. The ablation of either of the two timetable learning branches led to a drop in accuracy, suggesting that there is a synergistic effect between the two types of modeling, transformer-based and continuous-time modeling. Likewise, without the domain robustness mechanism, the performance on out-of-sample hospitals dropped, showing its value for cross-institution generalization.

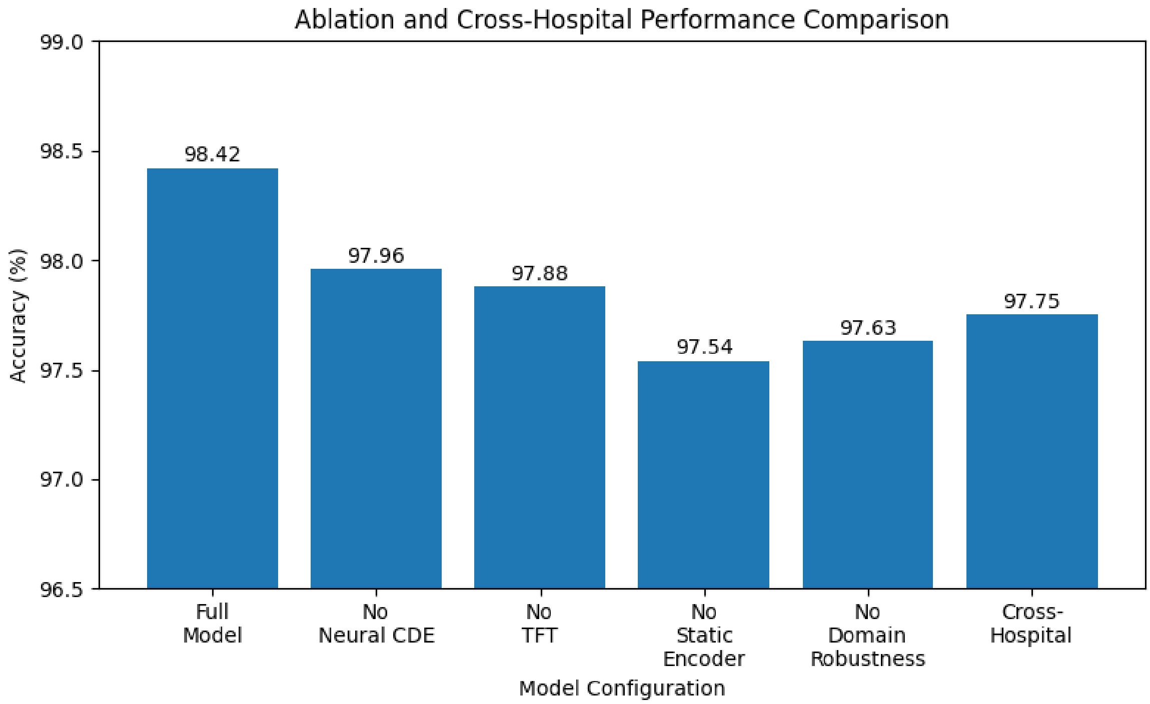

Figure 7: Ablation and cross-hospital performance comparison

In figure 7 shows model performance on various ablation settings and across unseen hospitals, highlighting the impact of each module on prediction accuracy and generalizability.

4.5 Discussion

The results of the experiments support the high predictive capacity of the suggested NeoTIDE framework in relation to different neonatal outcome tasks. The accuracy of the model was 98.42%, precision was 98.31%, recall was 98.27%, the F1-score was 98.29%, and the AUC was 98.65%, indicating it is a very good predictor of mortality for high-risk and low-risk neonatal cases. Similarly, prediction of respiratory failure had high accuracy and a recall of 98%, indicating that the temporal encoders have the ability to detect complicated physiological responses. The regression model performed well for length-of-stay prediction with small error and high correlation between the prediction and actual length in the ICU. The ablation analysis results also revealed that the Temporal Fusion Transformer combined with the Neural CDE and domain robustness module greatly decreased the predictive stability and cross-hospital generalization performance.

5 Conclusion and Future work

The study introduced a cloud-enabled explainable AI framework for neonatal risk prediction that can be used to aid early clinical decisions in neonatal intensive care. The proposed framework combines the static clinical data with the temporal physiological data by employing a dual-path temporal learning architecture called the Temporal Fusion Transformer (TFT) and Neural Controlled Differential Equation (Neural CDE) network. By combining these, the model is able to learn the long-range temporal dynamics and continuous-time physiology from the varied neonatal monitoring data. A multi-source representation fusion method based on temporal invariance was used to improve the robustness between the different healthcare institutions. Furthermore, the model is complemented by an Explainable Artificial Intelligence (XAI) module to make the model more interpretable and thus provide insights into the clinical factors influencing the prediction of neonatal outcome.

The proposed framework was tested experimentally using a multi-center neonatal ICU (NICU) database and was shown to be useful in predicting neonatal mortality risk, respiratory failure, and length of stay. The framework showed satisfactory predictive performance, while the generalization capability to unseen hospitals was excellent, and the stability of the ablation and generalization analyses was excellent across different hospitals. The findings also indicate the potential for transformer-based temporal modeling, continuous-time learning, and explainable analytics to provide accurate and clinically relevant assessments of neonatal risk. The cloud-based design also aids in scalable deployment, real-time monitoring, and provisioning of intelligent care in modern clinical environments.

Additional multimodal healthcare data streams can be added to the proposed framework, like medical imaging, genomic data, clinical notes, and bedside monitoring data. In the real world of healthcare, more trust and adoption could be gained by implementing the use of higher-level explainability techniques and visualization tools for the healthcare workers. Moreover, more geographically diverse and larger neonatal populations are required to validate the clinical use and further deploy it. Real-time hospital information system integration and edge-cloud healthcare infrastructures are other potential future advancements in next-generation intelligent neonatal decision-support systems.

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