# Predicting Length of Stay in Neonatal Intensive Care Unit (NICU)

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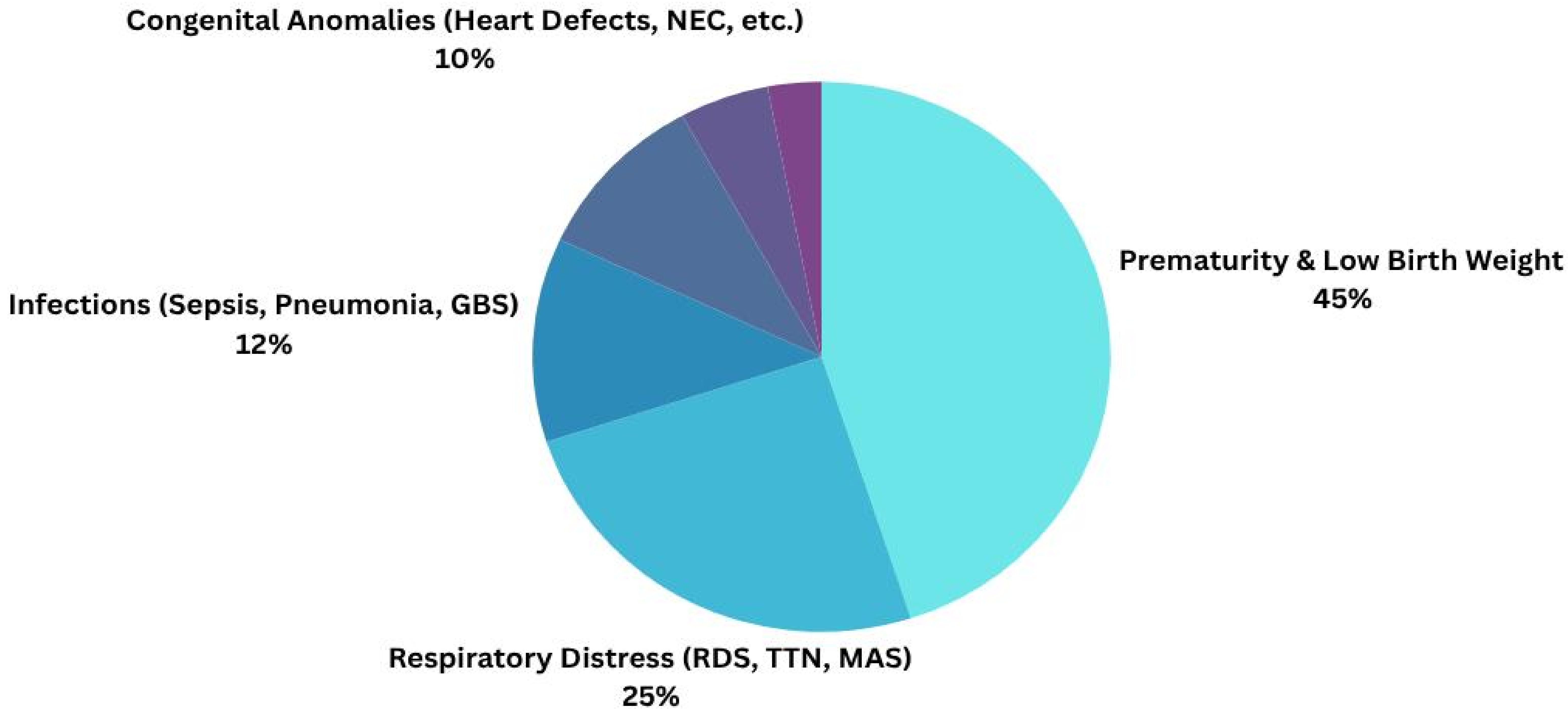
# Definition and Role of NICU (Neonatal Intensive Care Unit)

A specialized hospital unit providing intensive medical care for premature, low-birth-weight, or critically ill newborns.

# Main Roles of NICU

| | |
|---|---|
| **Specialized Care** | Continuous monitoring of vital signs using advanced equipment (ventilators, phototherapy). |
| **Nutritional Support** | Providing appropriate feeding through feeding tubes, breastfeeding, or a combination. |
| **Complication Management** | Treating common issues like apnea, jaundice, infections, and respiratory problems. |
| **Parental Support** | Offering education, counseling, and emotional support to parents facing stress and anxiety. |

# Reasons for Neonatal Admission to NICU



# What is LOS

# Definition of Length of Stay Prediction

Length of Stay (LOS) prediction refers to the process of

estimating the duration a patient will remain hospitalized,

especially in intensive care units like NICU.

It is a critical factor for healthcare planning, resource alloca

and improving patient outcomes.

# Why is LOS Prediction Challenging?

# Challenges

**Patient Variability**

Differences in patient conditions, such as prematurity, birth weight, and congenital disorders.

**Complexity of Medical Data**

Diverse sources (vital signs, lab results, medical history) make data integration difficult.

**Unpredictable Complications**

Sudden infections or other medical issues can prolong stay.

**Limited Data for Rare Conditions**

Insufficient data for accurate predictions in uncommon cases.

# Factors Affecting Length of Stay in NICU

## Clinical Factors

- Birth Weight
- Gestational Age
- Underlying Conditions
- Complications During Birth

## Non-Clinical Factors

- Resource Availability
- Hospital Protocols
- Socioeconomic Status
- Geographical Factors

# Impact and Benefits of LOS Prediction

### Resource Management:

- Optimized Staffing
- Efficient Bed Management
- Cost Control

### Treatment Planning:

- Personalized Care Plans
- Early Identification of High-Risk Cases
- Enhanced Coordination

### Parental Satisfaction

- Clear Expectations
- Reduced Anxiety
- Improved Communication

# The Role of Data and Artificial Intelligence in Healthcare and LOS Prediction

### Data Utilization

- Electronic Health Records
- Real-Time Monitoring
- Data Integration

### AI Applications

- Predictive Modeling
- Risk Stratification
- Automated Decision Support
- Natural Language Processing

### Benefits of AI in LOS Prediction

- Improved Accuracy
- Time Efficiency
- Enhanced Patient Outcomes

# Traditional Statistical Models in NICU


01 **Linear Regression**

Predicting continuous outcomes such as birth weight or length of stay in the NICU.

02 **Logistic Regression**

Predicting the likelihood of a neonate developing a specific condition (e.g., sepsis)

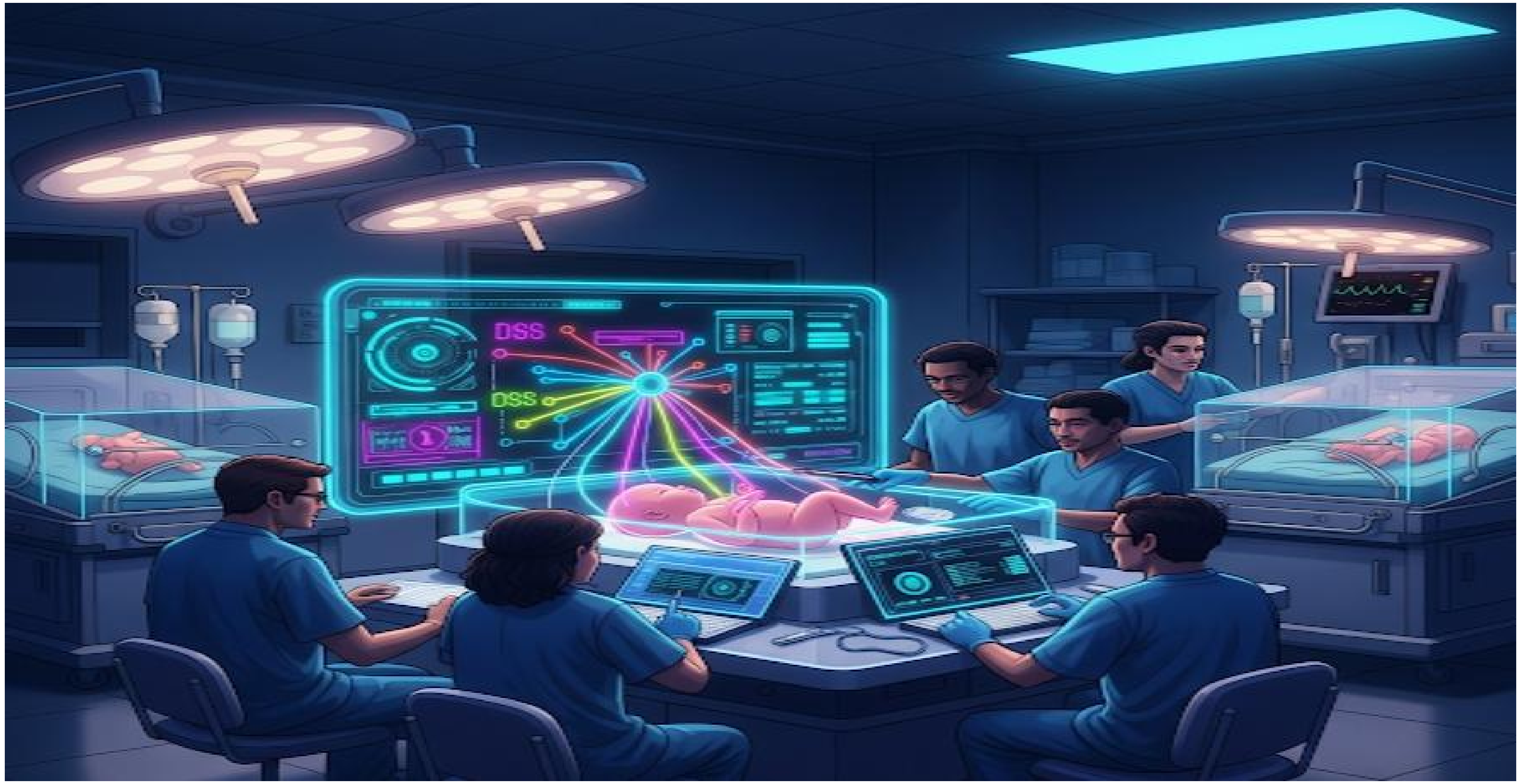
03 **Poisson Regression**

Predicting the number of complications or infections in the NICU.

04 **Cox Proportional Hazards**

Estimating the length of stay in NICU or the time to a specific clinical event.

# DSS



# Definition of Decision Support Systems (DSS)

**A Decision Support System (DSS) is a computer-based system that supports healthcare professionals in making informed clinical decisions by analyzing complex medical data.**

# Definition of Decision Support Systems (DSS)

## Components:

**Data Management**: Collects and stores patient data (EHRs, lab results, imaging).

**Model Management**: Utilizes algorithms (AI, machine learning) for data analysis.

**User Interface**: Provides a user-friendly interface for healthcare providers.

## Benefits:

**Improved Accuracy**: Reduces diagnostic errors.

**Time Efficiency**: Speeds up decision-making.

**Personalized Care**: Recommends treatments based on patient data.

# Types Of DSS

**Knowledge-Based Systems**

**Rely on medical guidelines and expert knowledge.**

**Non-Knowledge-Based Systems**

**Use machine learning to generate insights**

# Types of DSS Based on Rule-Based Approach

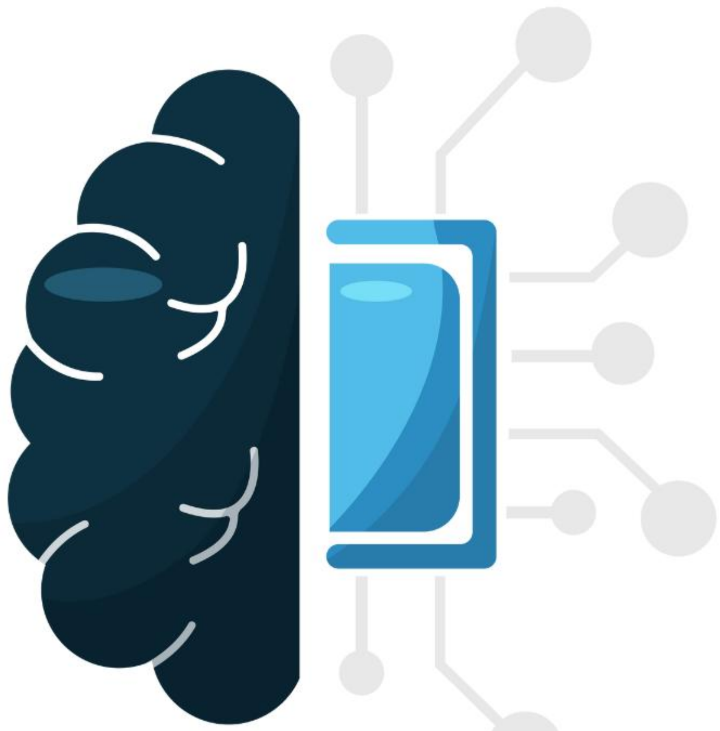
## Rule-Based

**Operate using predefined rules and clinical guidelines (IF-THEN logic).**

**Example:** "IF body temperature > 38□C, THEN suggest antipyretic medication."

**Advantages**: Transparent, easy to understand and modify**.**

**Limitations**: Limited to predefined rules, may not adapt to new conditions.



## Non-Rule-Based

**Use data-driven methods, including machine learning and AI, rather than fixed rules.**

**Example:** Predicting the risk of sepsis in neonates using a neural network.

**Advantages:** Can learn from data and improve over time.

**Limitations:** May lack transparency (black-box nature).

# Types of DSS Used in NICU

| Types | Definition | Example |
|---|---|---|
| **Clinical Decision Support Systems (CDSS)** | Provides diagnostic and treatment recommendations based on patient data | Suggesting antibiotic therapy for suspected neonatal sepsis |
| **Monitoring Decision Support Systems** | Analyzes real-time vital signs to detect abnormalities (heart rate, oxygen saturation). | Detecting respiratory distress or apnea in neonates. |
| **Predictive Decision Support Systems** | Utilizes machine learning models to forecast outcomes (length of stay, complications). | Predicting the risk of prolonged NICU stay for a premature infant. |
| **Medication Management Systems** | Recommends safe dosages of medications based on weight, age, and health status. | Adjusting antibiotic doses for low birth weight infants. |
| **Parental Guidance Systems** | Educates and supports parents with neonatal care instructions. | Interactive apps providing feeding and hygiene guidelines for parents. |

# Machine Learning

# Machine Learning Algorithms Used in NICU

**01** **Random Forest**

Predicting length of stay, risk of complications, and disease classification.

**02** **Support Vector Machine**

Classifying neonatal conditions (sepsis, respiratory distress)

**03** **XG Boost**

Predicting patient outcomes, disease risk, and NICU stay duration

**04** **K-Nearest Neighbors**

Predicting patient conditions based on similarity with historical cases.

# Deep Learning

# Deep Learning Algorithms Used in NICU

01 **Long Short-Term Memory**

Predicting time-series data such as patient vitals (heart rate, oxygen levels) over time

02 **CNN**

Analyzing medical images like X-rays, ultrasound scans, and CT scans

03 **Artificial Neural Networks**

Predicting neonatal outcomes like mortality, complications, and length of stay

04 **Generative Adversarial Networks**

Data augmentation for rare conditions, synthetic medical data generation.

# Article

# Article 1

Neural Computing and Applications (2024) 36:14433–14448
https://doi.org/10.1007/s00521-024-09831-7

ORIGINAL ARTICLE

Check for updates

## Machine learning-based prediction of length of stay (LoS) in the neonatal intensive care unit using ensemble methods

Ayse Erdogan Yildirim[1] · Murat Canayaz[2]

Received: 17 October 2023 / Accepted: 12 April 2024 / Published online: 7 May 2024

**STUDY GOAL**

To predict the length of stay (LoS) for neonates in NICU using machine learning algorithms for better resource and staff planning.

**METHODS**

- Retrospective study on 453 NICU patients in Turkey.
- Used 12 prenatal and clinical features from epicrisis reports.
- Applied multiple classifiers (RF, CatBoost, XGBoost, etc.).
- Developed a two-stage hybrid model CF-LoS using Voting Classifier.

**RESULTS**

- Random Forest achieved the highest accuracy: 97.7%.
- Soft Voting Classifier reached 96.3% accuracy and AUC: 0.947.
- LoS prediction supports NICU resource management and patient admission decisions.

# Article 2

International Journal of Medical Informatics
Volume 180, December 2023, 105267

## Developing a length of stay prediction model for newborns, achieving better accuracy with greater usability

Tzviel Frostig [a], Yoav Benjamini [a b], Orli Kehat [c], Ahuva Weiss-Meilik [c], Dror Mandel [d], Ben Peleg [e f], Zipora Strauss [e f], Alexis Mitelpunkt [e g]

**STUDY GOAL**

**To develop a robust and simple model for predicting NICU length of stay (LOS) for preterm infants using data available on the first day after birth.**

**METHODS**

**Data:** 5,263 preterm infants from one NICU and 8,858 from another for external validation.

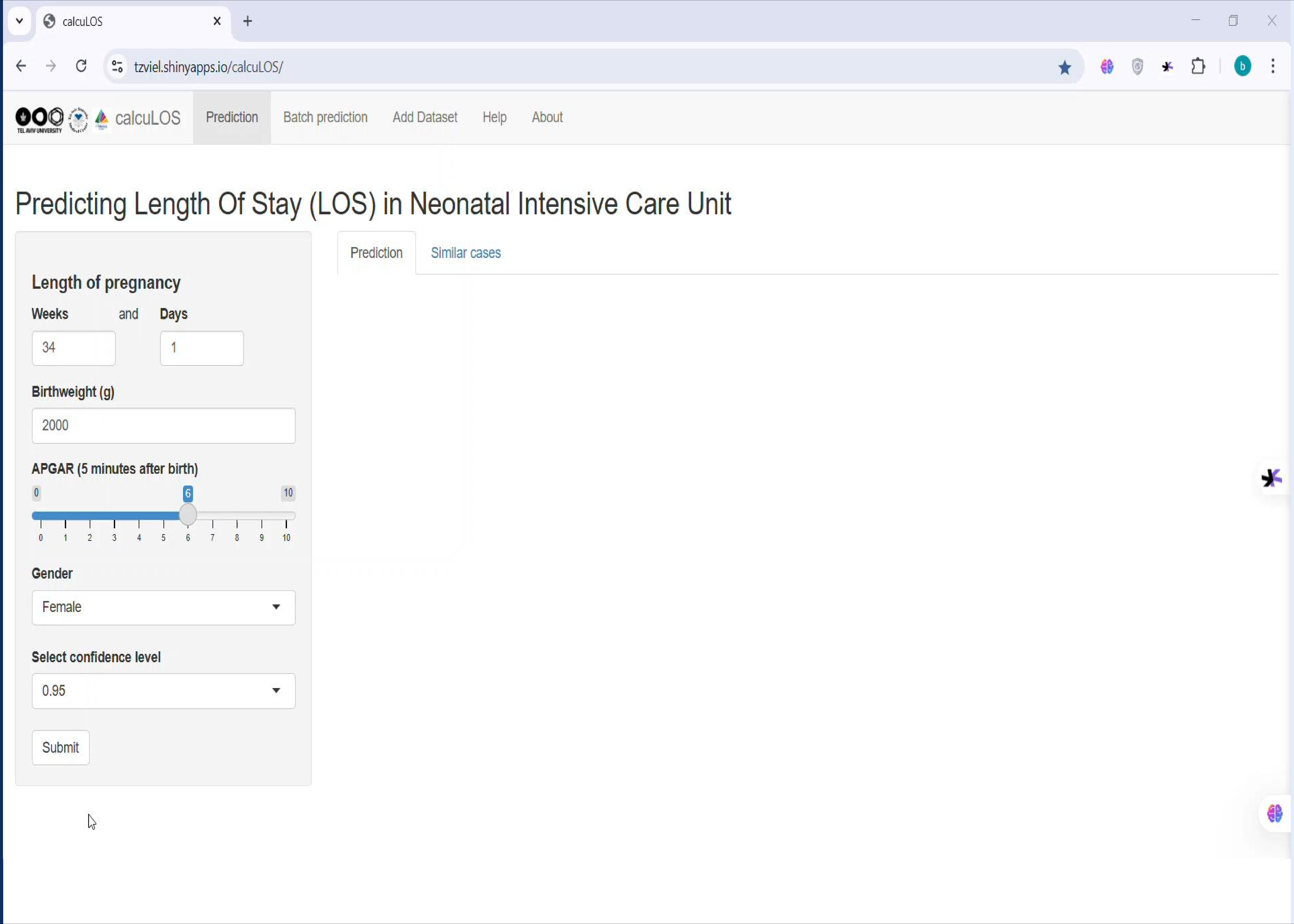
**Techniques:** Quantile Regression, Random Forest, XGBoost, and variable selection methods (LASSO, AIC, FDR).

Focused on a simplified model using only 4 features (GA, BW, APGAR, Sex).

Validated using 10-fold CV, test set, and external data.

**RESULTS**

- **MAE:** 6.26 days (internal), 6.04 days (external)
- **$R^2$: 0**.76 on external data
- Model is accurate, stable, interpretable, and accessible via an online tool (calcuLOS).
- Outperformed existing LOS prediction models in early prediction.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tzviel.shinyapps.io/calcuLOS/
calcuLOS
Prediction
Batch prediction
Add Dataset
Help
About
Predicting Length Of Stay (LOS) in Neonatal Intensive Care Unit
Length of pregnancy
Weeks
and
Days
34
1
Birthweight (g)
2000
APGAR (5 minutes after birth)
0
6
10
0 1 2 3 4 5 6 7 8 9 10
Gender
Female
Select confidence level
0.95
Submit
Prediction
Similar cases

# Article 3

scientific reports



Article | Open access | Published: 24 May 2023

## A case-based reasoning system for neonatal survival and LOS prediction in neonatal intensive care units: a development and validation study

Farzaneh Kermani, Mohammad Reza Zarkesh, Mostafa Vaziri & Abbas Sheikhtaheri

*Scientific Reports* **13**, Article number: 8421 (2023) | Cite this article

**STUDY GOAL**

**To develop and validate a web-based CBR system for predicting neonatal survival and length of stay (LOS) in NICUs.**

**METHODS**

**Dataset:** 1,682 neonatal cases with 17 variables (mortality) and 13 variables (LOS)

**Model:** K-Nearest Neighbor CBR system

Internal validation (336 cases), external validation (92 cases)

Usability and acceptability tested in a real hospital environment

**RESULTS**

**Survival prediction:**

**Accuracy**: 97.02% (internal), 98.91% (external)

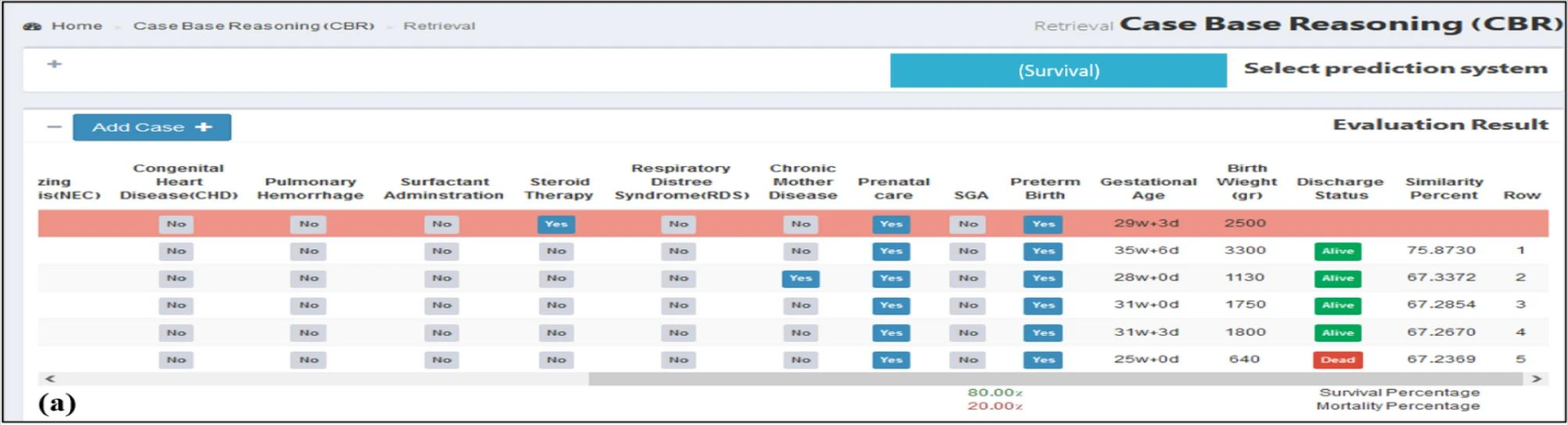
**F-score**: 0.984 → 0.993

**LOS prediction:**

**RMSE:** 4.78 days (internal), 3.27 days (external)

**Usability score (SUS):** 80.71

**High physician acceptance and trust in system predictions**



Home › Case Base Reasoning (CBR) › Retrieval

Retrieval **Case Base Reasoning (CBR)**

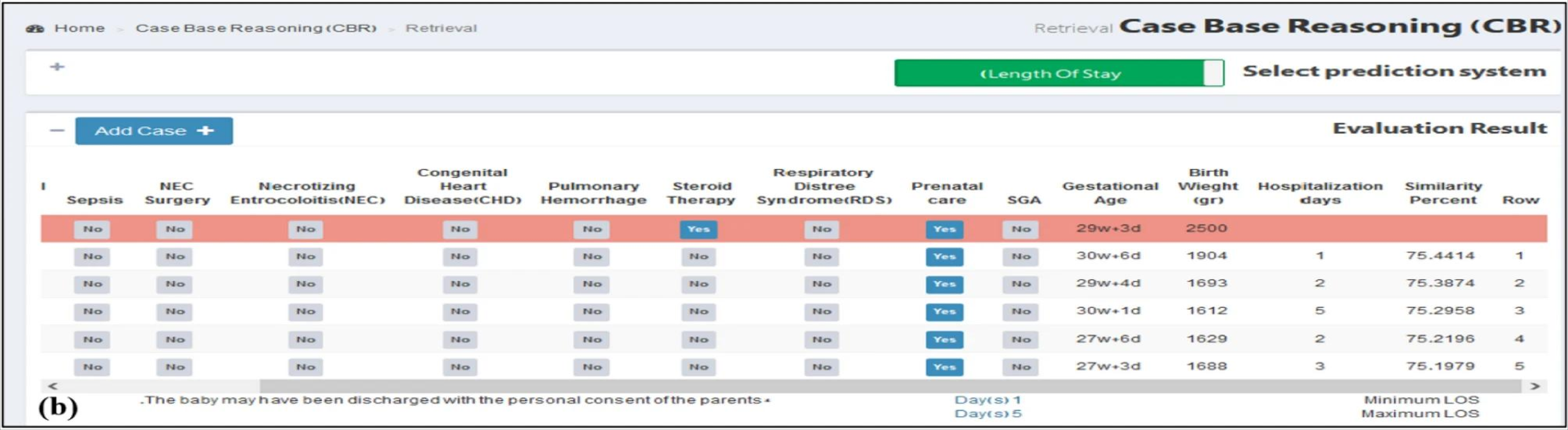
(Survival) Select prediction system

Add Case + **Evaluation Result**

| zing is(NEC) | Congenital Heart Disease(CHD) | Pulmonary Hemorrhage | Surfactant Adminstration | Steroid Therapy | Respiratory Distree Syndrome(RDS) | Chronic Mother Disease | Prenatal care | SGA | Preterm Birth | Gestational Age | Birth Wieght (gr) | Discharge Status | Similarity Percent | Row |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No | No | No | Yes | No | No | Yes | No | Yes | 29w+3d | 2500 | | | |
| | No | No | No | No | No | No | Yes | No | Yes | 35w+6d | 3300 | Alive | 75.8730 | 1 |
| | No | No | No | No | No | Yes | Yes | No | Yes | 28w+0d | 1130 | Alive | 67.3372 | 2 |
| | No | No | No | No | No | No | Yes | No | Yes | 31w+0d | 1750 | Alive | 67.2854 | 3 |
| | No | No | No | No | No | No | Yes | No | Yes | 31w+3d | 1800 | Alive | 67.2670 | 4 |
| | No | No | No | No | No | No | Yes | No | Yes | 25w+0d | 640 | Dead | 67.2369 | 5 |

80.00% Survival Percentage
20.00% Mortality Percentage

(a)



Home › Case Base Reasoning (CBR) › Retrieval

Retrieval **Case Base Reasoning (CBR)**

(Length Of Stay) Select prediction system

Add Case + **Evaluation Result**

| I | Sepsis | NEC Surgery | Necrotizing Entrocoloitis(NEC) | Congenital Heart Disease(CHD) | Pulmonary Hemorrhage | Steroid Therapy | Respiratory Distree Syndrome(RDS) | Prenatal care | SGA | Gestational Age | Birth Wieght (gr) | Hospitalization days | Similarity Percent | Row |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No | No | No | No | No | Yes | No | Yes | No | 29w+3d | 2500 | | | |
| | No | No | No | No | No | No | No | Yes | No | 30w+6d | 1904 | 1 | 75.4414 | 1 |
| | No | No | No | No | No | No | No | Yes | No | 29w+4d | 1693 | 2 | 75.3874 | 2 |
| | No | No | No | No | No | No | No | Yes | No | 30w+1d | 1612 | 5 | 75.2958 | 3 |
| | No | No | No | No | No | No | No | Yes | No | 27w+6d | 1629 | 2 | 75.2196 | 4 |
| | No | No | No | No | No | No | No | Yes | No | 27w+3d | 1688 | 3 | 75.1979 | 5 |

.The baby may have been discharged with the personal consent of the parents *

Day(s) 1 Minimum LOS
Day(s) 5 Maximum LOS

(b)

# Article 4

Journal of the Formosan Medical Association
Volume 121, Issue 6, June 2022, Pages 1141-1148

Original Article

## Predicting in-hospital length of stay for very-low-birth-weight preterm infants using machine learning techniques

Wei-Ting Lin [a], Tsung-Yu Wu [a], Yen-Ju Chen [a], Yu-Shan Chang [a], Chyi-Her Lin [a b], Yuh-Jyh Lin [a]

STUDY GOAL

**Predict hospital length of stay (LOS) in VLBW preterm infants using machine learning.**
**Compare performance of different ML algorithms.**

METHODS

Retrospective cohort of 3519 infants from Taiwan Neonatal Network (2016–2018).
21 clinical features used.
**Outcome**: continuous (LOS) and categorical (late vs. non-late discharge).
**Algorithms**: Linear Regression, MLP, SVM, KNN, REPTree, Random Forest.
10-fold cross-validation.

RESULTS

- Median LOS: 61 days.
- 59% of deaths occurred within first 7 days.
- Poor performance for continuous LOS ($R^2 < 0.6$).
- Best classification performance:
  - Logistic Regression (AUC: 0.724)
  - Random Forest (AUC: 0.712)

# Article 5

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## A High-Fidelity Model to Predict Length of Stay in the Neonatal Intensive Care Unit

Kanix Wang, Walid Hussain, John R. Birge, Michael D. Schreiber, Daniel Adelman

Published Online: 30 Aug 2021 https://doi.org/10.1287/ijoc.2021.1062

**STUDY GOAL**

**Develop an interpretable dynamic model to predict remaining LOS in NICU**

**METHODS**

Used EMR data of 4624 discharges (2008–2015).

Built dynamic survival models with Random Survival Forest (RSF).

Involved neonatologists to define health variables.

Rolling predictions based on daily updates.

**RESULTS**

Test $R^2 > 0.8$ after 55% of patients discharged.

Outperforms AFT and LSTM models.

AUC > 0.88 for 7/14/30-day discharge prediction.

**Key predictive features**: gestational age (day 0), feeding and respiratory status (day 7/14).

Enables census prediction and real-time resource planning.

# THANK YOU!