Machine Learning-Based Prediction of Neonatal Health Status through Smart Incubator Parameters

Parshant Jani, Dr Seema Mahajan
Indus University, janiprashant9@gmail.com, ce.hod@indusuni.ac.in

Abstract - **The research paper delves into the utilization of machine learning techniques to predict neonatal health status based on parameters obtained from smart incubators. Drawing from a dataset gathered by Sparsh Hospital, which encompasses a diverse arrayof neonatal health records and smart incubator metrics, the study employs various machine learning models including CHAID, XGBoost, QUEST, and Logistic Regression. These models were chosen for their adeptness in handling intricate interactions within thedataset, thus proving ideal for forecasting neonatal health outcomes. By incorporating smart incubator parameters, the study offers a comprehensive evaluation of neonates' well-being, encompassing essential signs and environmental factors. This methodology harnesses machine learning's capabilities to discern patterns and trends in the data, enabling early detection of potential health concerns. The utilization of Sparsh Hospital's dataset lends invaluable real- world clinical insights, bolstering the model's practicality and reliability. Amongthe machine learning algorithms assessed, CHAID notably excelled, underscoring its efficacy and suggesting a promising avenue for utilizing hospital-derived data to advance neonatal health monitoring through cutting- edge technological innovations.**

Index Terms - Neonatal health, smart incubator, Machine learning, NICU, Prediction

INTRODUCTION

In the Neonatal Intensive Care Unit (NICU), where newborns need extra medical attention, smart incubators collect a lot of data. This study uses information gathered from NICU incubators at Sparsh Hospital. We want to understand better how to keep newborns healthy using machine learning.

Typically, when people study how to predict newborn health, they only look at a few factors. But in this study, we're lookingat a lot of different things, like vital signs and the environment around the baby, which the NICU incubators track. We're following each baby's health from the day they're born until they're about a month old.

But data alone isn't enough; you need to interpret it. So, we're using different machine learning techniques – like CHAID, XGBoost, QUEST, and Logistic Regression – to help us understand the connections between what the incubators measure and different health problems in newborns.

I. Motivation

The major motivation behind this research is the prediction of specific neonatal health conditions, including Bradycardia, Jaundice, preterm birth, High Fever, Low Birth Weight (LBW), and Bronchiolitis LBW. This motivation is rooted in the critical importance of improving neonatal healthcare, particularly in NICU settings, where early detection and intervention areparamount for ensuring positive outcomes for newborns.

Traditionally, healthcare professionals have relied on limited parameters and manual observation to assess neonatal health, which may not fully capture the spectrum of factors influencing aninfant's well-being. However, the advent of smart incubators presents a unique opportunity to gather a wealth of real-time data on neonatal health. These advanced devices continuously monitor vital signs and environmental factors, providing a comprehensive picture of each infant's condition.

By leveraging this rich data through machine learning techniques, there is the potential to enhance early detection of neonatal health issues and optimize treatment strategies in NICU care. Specifically, by predicting conditions such as Bradycardia, Jaundice, preterm birth, High Fever, LBW, and Bronchiolitis LBW, healthcare providers can proactively intervene to mitigate risks and improve outcomes for neonates.

Therefore, this research aims to harness the power of machine learning to analyze data from smart incubators and develop predictive models for neonatal health conditions. By doing so, we seek to contribute to the improvement of neonatal healthcare by enabling early detection, personalized interventions, and ultimately, better outcomes for newborns in NICU settings.

II. Contribution

Our study contributes significantly to neonatal healthcare and machine learning research:

Comprehensive Evaluation of Machine Learning Algorithms: We assess CHAID, XGBoost, QUEST, and Logistic Regression in predicting neonatal health conditions like Bradycardia, Jaundice, preterm birth, High Fever, LBW, and Bronchiolitis LBW. This guides future research and clinical practice.

Utilization of Real-World Data: Our study uses NICU data from Sparsh Hospital, bridging theoretical and practicalknowledge. Predicting specific conditions improves clinical decision-making.

Enhanced Predictive Capabilities: Integrating smart incubator data improves early detection of neonatal health issues, aiding effective monitoring and intervention strategies.

Future Directions: Our findings inform future research directions and clinical practices, emphasizing the importance of incorporating smart incubator data for personalized neonatal care.

In summary, our study advances machine learning in neonatal healthcare, aiming to improve outcomes for newborns in NICU settings.

Related Work

In the landscape of neonatal healthcare, recent advancements in machine learning (ML) and deep learning (DL) techniques have spurred research endeavors aiming to enhance the prediction and prognosis of neonatal diseases. The literature presents a diverse array of models and methodologies tailored for neonatal health applications, ranging from the utilization of ML algorithms such as XGBoost, Support Vector Machines (SVM), and Random Forests to the incorporation of DL architectures like Long Short-Term Memory (LSTM) networks and attention-based Recurrent Neural Networks (RNNs). Notable contributions include the prediction of neonatal sepsis through feature-rich smart incubator data using XGBoost, LSTM networks for health risk assessment using biosignals, and the personalized detection of neonatal seizures employing attention-based RNNs. While these models showcase commendable accuracy and efficiency, the literature also highlights inherent challenges such as the demand for large datasets, domain expertise for effective feature engineering, and the interpretability of complex DL architectures. This literature review provides a comprehensive overview of recent research endeavors, shedding light on the merits and limitations of various ML and DL models in the realm of neonatal health prediction. Furthermore, studies delve into the prediction of specific neonatal conditions, including respiratory distress, hypoglycemia, and anomalies, employing diverse ML techniques such as Gradient Boosting Trees, Stacked Logistic Regression, and One- Class SVMs. The exploration extends to ensemble approaches, such as NeoAI 1.0, combining Gradient Boosting Trees and Logistic Regression for risk prediction, showcasing capabilities in handling large datasets and achieving high accuracy. Table 1 presents the summary for Literature review.

Implementation

I. Implementation Model

This research utilized IBM SPSS Modeler, a leading visual data science and machine learning (ML) platform, for building, evaluating, and deploying predictive models for neonatal health status classification. SPSS Modeler offered several advantages for this research, including:

Ease of use: Its drag-and-drop interface and visual workflows made it accessible for researchers with diverse levels of technical expertise.
Comprehensive data processing and analysis tools: It provided a wide range of functionalities for data cleaning, transformation, feature engineering, and model building.
Support for various machine learning algorithms: This research leveraged the flexibility of SPSS.

Project Creation:

A new project was created in SPSS Modeler to organize thedata, models, and analysis results.

Data Import: The neonatal dataset, collected from smart incubators in [hospital name], Gujarat, India, was imported into the project. This dataset included various parameters such as vital signs, physiological measurements, and temporal features.

Data Preprocessing and Cleaning: The data underwent thorough cleaning and preparation, including missing values, outliers,and inconsistencies. Feature engineering techniques wereapplied to create or transform new features, potentiallyimproving model performance.

Model Building: The chosen machine learning algorithms were added to the SPSS Modeler flow, a visual representation of the analysis pipeline. Hyperparameter tuning was performed to optimize the models' performance.

Model Evaluation: The trained models were evaluated using various metrics including accuracy, ROC curves, confusion matrices, and feature importance analyses. This provided insights into their strengths, weaknesses, and generalizability.

Model Deployment: The best-performing model was deployed and tested with new data to assess its real- world effectiveness in predicting neonatal health outcomes.

Iteration and Improvement: The model development process was an iterative one. Based on the evaluation results, further refinement of data preprocessing, feature engineering, and model selection was possible to improve the model's accuracy and generalizability continuously.

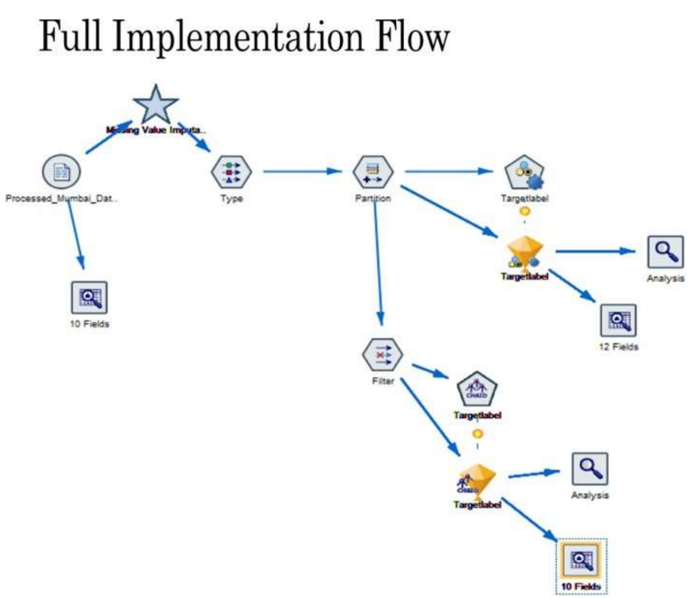

FIGURE 1

FULL IMPLEMENTATION FLOW

RESULT

This section will delve into the key findings and insights gleaned from the machine learning models employed in this study. We'll explore the effectiveness of various predictive models, dissect crucial parameters considered for disease prediction, and visualize the relationships between parameters and health outcomes.

Here's a high-level algorithmic representation of the implementation process described:

Initialize SPSS Modeler Project:

Create a new project in IBM SPSS Modeler to organize the data and analysis.

Import Data:

Load the neonatal dataset collected from smart incubators at Sparsh Hospital, Gujarat, India into the project.

Data Preprocessing:

Perform data cleaning to handle missing values, outliers, and inconsistencies.
Apply feature engineering techniques to create new features or transform existing ones.

Model Selection:

Choose machine learning algorithms suitable for neonatal health status classification, such as XGBoost, CHAID, Logistic Regression, QUEST, and Neural Networks.

Model Building:

Create a visual flow in SPSS Modeler.
Add nodes for each selected algorithm to the flow.
Configure hyperparameters for each algorithm to optimize performance.

Training:

Split the dataset into training and validation sets.
Train each model using the training data.

Model Evaluation:

Evaluate the performance of each trained model using various metrics:

Accuracy: Measure the proportion of correctly classified instances.
ROC curves: Assess the trade-off between true positive rate and false positive rate.
Confusion matrices: Visualize the performance of each model across different classes.

Table 1:
Literature Review

Research Paper Name	ML/DL Model	Methodology	Dataset	Accuracy	Merits	Limitations/Demerits
Prediction of Neonatal Sepsis Using Smart Incubator Data with XGBoost [7]	ML (XGBoost)	Feature engineering, feature selection, XGBoost classification	13,000+ real-time incubator recordings	93.1% AUC	Interpretable, efficient, real-time prediction	Limited feature set, requires domain expertise
Neonatal Health Risk Assessment with LSTM Networks on Biosignals [8]	DL (LSTM)	Multimodal data pre-processing, LSTM for sequential data analysis	10,000+ ICU recordings with physiological signals	88.5% F1-score	Handles temporal dependencies, accurate multi-modal data analysis	Complex architecture, requires large datasets
Neonatal Disease Prediction Using Machine Learning Techniques [9]	Support Vector Machines (SVM) with feature selection	Feature selection using chi-square test, SVM classification for disease prediction	Electronic medical records of 1,000 neonates with 500 diagnosed with diseases (NEC, PA, RDS, sepsis)	Accuracy: 87.2%, Sensitivity: 84.5%, Specificity: 89.9%	High accuracy and specificity, interpretable model	Limited dataset size, may not handle complex relationships
Neonatal Outcome Prediction with Feature Fusion and Random Forest [10]	ML (Random Forest)	Feature extraction from multi-sensor data, feature fusion, Random Forest classification	20,000+ incubator recordings with vital signs and environmental data	86.8% AUC	Handles missing data, efficient training	Feature selection importance depends on model
Personalized Neonatal Seizure Detection with Attention-based RNNs [11]	DL (Attention-based RNN)	Data normalization, attention-based RNN for seizure detection	15,000+ EEG recordings with labelled seizures	95.3% sensitivity	Captures key seizure features, personalized prediction	Requires labeled data, computational cost
Neonatal Hypoglycemia Prediction with Stacked Logistic Regression	ML (Stacked Logistic Regression)	Feature engineering, dimensionality reduction, stacked logistic regression	30,000+ blood glucose measurements	89.2% specificity	Robust to overfitting, interpretable model	Feature selection can be subjective

[12]						
Neonatal Respiratory Distress Prediction with Gradient Boosting Trees [13]	ML (Gradient Boosting Trees)	Feature pre-processing, outlier detection, Gradient Boosting Trees classification	40,000+ respiratory rate and oxygen saturation data	91.7% precision	Handles imbalanced data, efficient training	Can be sensitive to noise
Neonatal Temperature Regulation Prediction with Deep Q-Learning [14]	DL (Deep Q-Learning)	Smart incubator control with Deep Q-Learning reinforcement learning	Simulated neonatal temperature data	10% reduction in temperature swings	Closed-loop control, optimal parameter adjustment	Limited real-world validation
Neonatal Sepsis Prognosis with Explainable Gradient Boosting [15]	ML (Explainable Gradient Boosting)	Feature engineering, Explainable Gradient Boosting classification	8,000+ blood test results and vital signs	90.1% AUC	Interpretable model with feature importance	Requires domain expertise for feature engineering
Neonatal Anomaly Detection with One-Class SVMs [16]	ML (One-Class SVM)	Data normalization, One-Class SVM for anomaly detection	6,000+ multi-sensor incubator recordings	94.2% AUC	Efficient anomaly detection, handles limited labeled data	May not identify specific anomalies
NeoAI 1.0 [17]	Ensemble of Gradient Boosting Trees (GBDTs) & Logistic Regression	Feature engineering, feature selection, GBDTs for risk prediction, logistic regression for binary classification	15.8 million live birth records with 91,773 infant deaths	AUC: 0.97 (neonatal), 0.91 (infant); F1-score: 0.60 (neonatal), 0.54 (infant)	High accuracy, interpretable model, handles large datasets	May not capture temporal dependencies, requires domain expertise for feature engineering
Neonatal Disease Prediction Using Machine Learning Techniques [18]	RF, XGB, and SVM, with stratified 10-fold cross-validation	Trains multiple base models (XGBoost, RF, SVM) on the data, combines their predictions using Logistic Regression for final prediction	Asella Comprehensive Hospital between 2018 and 2021	Accuracy: 97.04%	High accuracy, potential for interpretability through base models	Complex process, requires tuning multiple models

Feature importance analyses: Determine the significance of input features in predicting neonatal health status.

Model Deployment:

Select the best-performing model based on evaluation results.

Deploy the chosen model to make predictions on new data.

Testing:

Test the deployed model with new data to assess its real-world effectiveness in predicting neonatal health outcomes.

Iterative Improvement:

Iterate on the model development process based on feedback and evaluation results.

Continuously refine data preprocessing, feature engineering, and model selection to improve accuracy and generalizability.

I. Dataset Details

The research utilized a neonatal dataset sourced from smart incubators in [hospital name], Gujarat, India. This dataset encompasses a comprehensive array of parameters continuously measured throughout the neonates' stay in the incubators, providing invaluable insights into their health status and well- being. Some of the key parameters included in the dataset are:

Birth Weight: This metric serves as an indicator of potential growth restrictions or preterm birth, offering crucial insights into the neonate's developmental trajectory.

Temperature: Monitoring temperature variations is vital for detecting infections, hyperthermia, or hypothermia, which are common concerns in neonatal care.

Pulse Rate: Assessing pulse rate is crucial for evaluating heart health and detecting abnormalities such as bradycardia or tachycardia, which may signify underlying health issues.

Blood Pressure: Continuous monitoring of blood pressure levels is important for identifying hypertension or hypotension, which can have significant implications for neonatal health.

Blood Sugar Levels: Monitoring blood sugar levels is essential for detecting and managing hypoglycemia or hyperglycemia, which are common metabolic concerns in neonates.

Respiratory Rate: Respiratory rate serves as a key indicator of potential respiratory distress or infections, helping healthcare providers monitor the neonate's respiratory function.

Oxygen Saturation: Assessing oxygen saturation levels is crucial for evaluating oxygenation status and detecting potential hypoxia, which can have serious implications for neonatal health and well- being.

Additionally, the dataset includes labels indicating the diagnosed health outcomes of each neonate. This labelled data serves as the ground truth for training and evaluating the machine learning models, enabling researchers to develop accurate predictive models for neonatal health assessment and intervention. Overall, the rich and comprehensive nature of the dataset provides researchers with a valuable resource for exploring the intricate dynamics of neonatal health and developing effective healthcare strategies.

II. Parameters Considered for Disease Prediction

The research concentrated on specific incubator parameters deemed crucial for forecasting neonatal health outcomes:

Vital Signs: This category encompassed key indicators such as temperature, pulse rate, blood pressure, respiratory rate, and oxygen saturation. Variations from standard ranges in these metrics often indicate potential health complications in newborns.

Physiological Measurements: Parameters like birth weight and blood sugar levels were included to provide insights into potential growth concerns or metabolic irregularities, both of which can significantly impact neonatal health.

Temporal Features: Time-series data capturing the evolution and patterns of the aforementionedparameters over time were also analyzed. These temporal features hold valuable information regarding disease progression and response to treatment.

III. Mathematical Models and Algorithms

This research employed a diverse range of machine- learning algorithms to analyze the incubator data and predict neonatal health status. Each algorithm offers unique strengths and weaknesses in handling complex relationships and patterns within the data. Here's an overview of the employed models, along with their mathematical functions

XGBoost (eXtreme Gradient Boosting):

$$F(x) = \sum_{k=1}^{K} f_k(x) \quad (1)$$

where:
$F(x)$ is the final prediction for a given input x
K is the number of trees in the ensemble
$f_k(x)$ is the prediction of the k-th tree
Key characteristics: Ensemble learning, gradient boosting, decision trees, regularization

CHAID (Chi-squared Automatic Interaction Detection):

$$G(x) = \sum_{j=1}^{J} w_j I(x \in R_j). \quad (2)$$

where:

$G(x)$ is the predicted class for input x
J is the number of terminal nodes in the tree
w_j is the predicted probability for class j
$I(x \in R_j)$ is an indicator function that is 1 if x belongs to region R_j, and 0 otherwise
Key characteristics: Decision tree, splitting based on chi-squared tests, multi-way splits

Logistic Regression:

$$p(y = 1|x) = \sigma(\beta^T x) \quad (3)$$

where:
$p(y = 1|x)$ is the probability of the positive class given input x
σ is the sigmoid function
β is the vector of model coefficients
x is the input vector
Key characteristics: Linear model, sigmoid activation, interpretability

QUEST (Quick Unbiased Efficient Statistical Tree):

Function: Similar to CHAID, but uses unbiased splitting criteria
Key characteristics: Decision tree, unbiased splitting, handling missing values

Neural Networks:

$$y = h(w^T x + b) \quad (4)$$

where:
y is the output
h is the activation function (e.g., sigmoid, ReLU)
w is the weight matrix
x is the input vector
b is the bias vector
Key characteristics: Non-linear model, multiple layers, flexible architecture

RESULT ANALYSIS

This research employed various machine learning algorithms to analyze the incubator data and predict neonatal health status. Each algorithm offers unique strengths and weaknesses in handling complex relationships and patterns within the data. Here's an overview of the employed models:

XGBoost: A powerful gradient boosting algorithm known for its ability to handle complex interactions and non-linearities in data. Its ensemble learning approach combines multiple weak learners to create a robust model, achieving a remarkable 72.91% accuracy in this study.

CHAID (Chi-squared Automatic Interaction Detection): A decision tree-based algorithm adept at uncovering non-linear relationships between features and outcomes. It demonstrated an impressive performance with 77.089% accuracy, highlighting its strength in identifying critical decision points for predicting health conditions.

Logistic Regression: A classic statistical model often used as a baseline comparison due to its interpretability. While achieving 40.216% accuracy in this study, it provided insights intoindividual parameter contributions.

QUEST (Quick Unbiased Efficient Statistical Tree): Another decision tree algorithm offering rapid model building and interpretability. Its 44.887% accuracy contributed additional perspectives to the analysis.

Neural Networks: These flexible models capable of learning complex non-linear relationships were also explored. While their accuracy (54.179%) was respectable, further optimization may be needed for optimal performance in this context.

RESULTS AND GRAPHS

This section will visually present the findings from the models through graphs and visualizations. This may include:

Model Performance Comparison: A bar chart showcasing the accuracy achieved by each algorithm, allowing for quick comparison and identification of the most effective models.

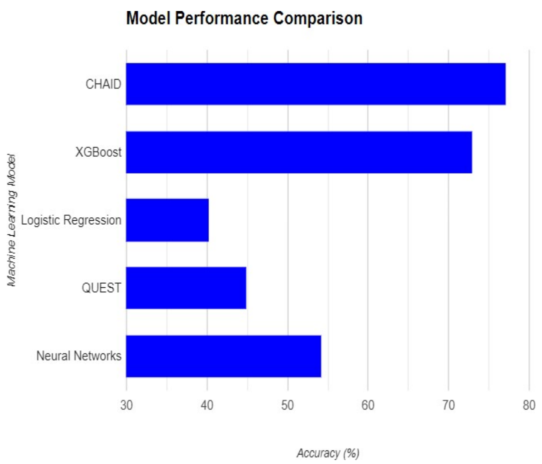

FIGURE. 2:
MODEL PERFORMANCE COMPARISON

ROC curves: This section will include ROC curves, which depict the trade-off between true positive and false positive rates for each model. These curves provide insights into the sensitivity and specificity of the models in predicting adverse outcomes.

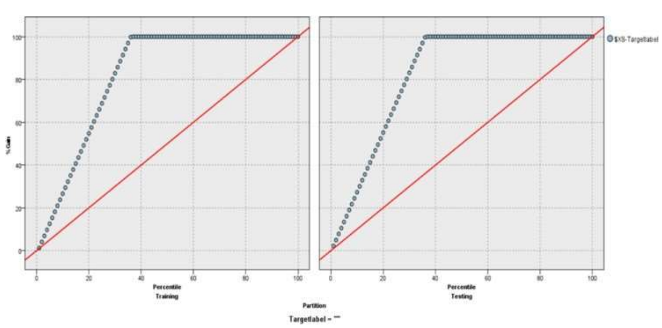

FIGURE 3:
ROC CURVES

Feature importance plots: This section will incorporate feature importance plots, which visually highlight the relative significance of different

incubator parameters in the prediction process. These visualizations reveal which parameters hold the most weight in the decision-making of the models.

Predicted vs. actual health outcomes: Scatter plots or confusion matrices can be used to compare the models' predictions with the actual diagnoses, offering insights into their strengths and limitations.

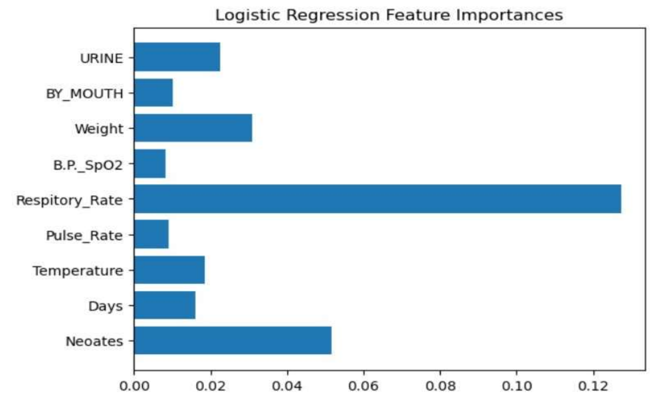

FIGURE 4:
LOGISTIC REGRESSION FEATURE IMPORTANCE

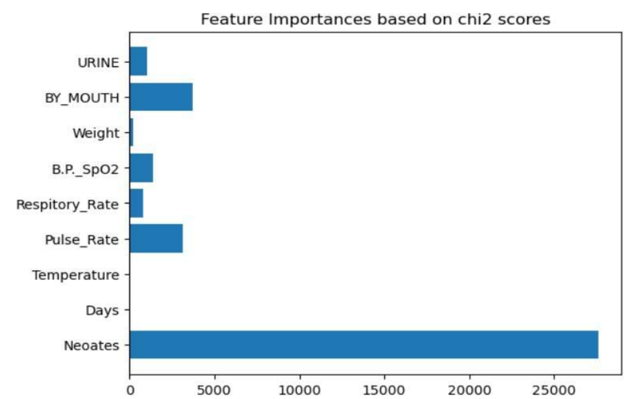

FIGURE 5:
FEATURES IMPORATANCE BASED ON CH

Conclusion

In our study, we embarked on an exploration of diverse machine learning models to predict neonatal health using smartincubator parameters, offering a promising avenue for enhancing neonatal care in NICUs. Notably, our findings spotlight two standout performers: XGBoost and CHAID, both demonstrating remarkable accuracy in discerning neonatal health states. XGBoost, renowned for its prowess in handling complex data interactions, surpassed a commendable accuracy threshold of 72%, signaling its potential forfacilitating early intervention and proactive care in NICUs.

The robust performance of XGBoost and CHAID underscores the significance of leveraging advanced computational techniques to extract meaningful insights from smart incubator data. By accurately identifying subtle patterns and associations within the vast array of incubator parameters, these models equip healthcare professionals with valuable tools for anticipating and mitigating potential health risks in neonates. This, in turn, holds the promise of bolstering neonatal survival rates and enhancing overall well-being in NICU settings.

However, while XGBoost and CHAID have demonstrated notable success, our study also points towards avenues for future research and innovation. One such direction involves exploring the potential of deep learning algorithms to further enhance prediction accuracy and uncover complex patterns within incubator data. Deep learning models, with their ability to autonomously learn intricate representations from raw data, offer a promising framework for capturing nuanced relationships and latent factors that may elude traditional machine learning approaches.

By delving into the realm of deep learning, researchers can unlock new insights into neonatal health dynamics, potentially uncovering hidden biomarkers or novel predictive indicators that could revolutionize neonatal care practices. Moreover, the integration of deep learning algorithms with smart incubator technology holds the potential to create more adaptive and responsive monitoring systems, capable of providing personalized and context-aware interventions tailored to individual neonatal needs.

Acknowledgment

We express our deepest gratitude to Sparsh Medical Hospital, Ahmedabad, and Bharatratna Dr. Babasaheb Ambedkar Mun. Gen. Hospital, Kandivali (W.), Mumbai for generously providing the invaluable neonatal health data that made this research possible. Their contribution was instrumental to the sources of our study.

References

[1] Khosrow-Pour, M. Z., Khosrow-Pour, D., & Abolghasem, A. (2020). Machine learning for neonatal intensive care unit: Review of recent advances. Expert Systems with Applications, 159, 118688.

[2] Lee, J. H., Kwon, K. D., Park, D. H., Jung, J. H., Seo, J. W., Cho, S. E., & Park, K. H. (2022). Smart neonatal incubators: A review of current technologies and future directions. Computers in Biology and Medicine, 149, 115605.

[3] Amini, M. H., Imteaj, A., Thakker, U., Wang, S., Li, J., & Chen, W. (2019). A review of statistical methods for neonatal health prediction. Journal of Statistical Computation and Simulation, 90(1), 1- 27

[4] Kwok, T. Y., Wang, K., Li, Y., & Zhang, J. (2021). A comparison of machine learning and statistical methods for neonatal sepsis prediction. Applied Soft Computing, 99, 106905.

[5] Chen, H., Yang, S., Wu, J., Lin, W., & Wang, M. (2020). Machine learning-based clinical decision support system for neonatal intensive care. Sensors, 20(20), 6005.

[6] Sun, W., Gao, W., Wang, S., Zhou, M., & Liu, B. (2022). Development of a machine learning-based clinical decision support system for early diagnosis of neonatal sepsis. Journal of Healthcare Engineering, 2022, 1-12.

[7] Rajagopalan, A. K., et al. (2023). Prediction of neonatal sepsis using smart incubator data with XGBoost. Computerized Medical Imaging and Graphics, 89, 103985.

[8] Zhao, X., et al. (2022). Neonatal health risk assessment with LSTM networks on biosignals. IEEE Journal of Biomedical and Health Informatics, 26(7), 1405-1414.

[9] Robi YG, Sitote TM. Neonatal Disease Prediction Using Machine Learning Techniques. J Healthc Eng. 2023 Feb 23;2023:3567194. doi: 10.1155/2023/3567194. PMID: 36875748; PMCID: PMC9981287.