PREDICTING THE UNPREDICTABLE: A DATA DRIVEN-APPROACH TO NEONATAL CARDIAC ARREST

A. VARSHA SREE
(Dept. of CSE, Siddhartha Institute of Technology and Sciences)
21tq1a6744@siddhartha.co.in

N. BHARGAVI
ASSISTANT PROFESSOR
(Dept. of CSE, Siddhartha Institute of Technology and Sciences)
bhargavi.cse@siddhartha.co.in

A. ANKITH REDDY
(Dept. of CSE, Siddhartha Institute of Technology and Sciences)
21tq1a6740@siddhartha.co.in

B. SUSHANTH
(Dept. of CSE, Siddhartha Institute of Technology and Sciences)
21tq1a6747@siddhartha.co.in

K. ACHYUTH
(Dept. of CSE, Siddhartha Institute of Technology and Sciences)
21tq1a6716@siddhartha.co.in

Abstract—**Neonatal cardiac arrest, a critical condition in babe, presents significant challenges due to its unforeseen onset and potentially severe issues. the ideal of this design is to develop a prophetic model for early discovery of cardiac arrest in babes using a data- driven approach. by assaying expansive clinical and physiological datasets collected from neonatal ferocious care units(NICUs), this study aims to identify crucial pointers and trends antedating cardiac arrest occurrences. the methodology integrates machine literacy algorithms with point engineering to punctuate physiological parameters similar as heart rate variability, oxygen achromatism, blood pressure, and respiratory patterns. data preprocessing ways are employed to handle noise and missing values, while machine literacy algorithms similar as logistic retrogression, arbitrary timbers, and neural networks are trained to classify high- threat cases. point significance analysis is conducted to understand the critical factors contributing to cardiac arrest prognostications. primary results demonstrate that the model can achieve significant delicacy. eventually, our data- driven approach to prognosticating neonatal cardiac arrest represents a promising advancement in neonatal healthcare, fastening on forestallment and perfection care.**

Keywords—Cardiac arrest, intensive care unit, machine learning, neonates.

Introduction

Cardiac arrest in newborns is a critical medical emergency with the potential for life-threatening outcomes, including severe complications and death. Timely recognition of this condition is essential for ensuring appropriate care and improving the long-term health prospects of affected infants. Identifying the warning signs and understanding the associated risk factors are key to early detection and prevention of cardiac arrest in neonates. Common indicators of cardiac arrest in newborns include a rapid heart rate, respiratory difficulties, bluish discoloration of the skin, lack of responsiveness, and reduced physical activity. Immediate medical attention is necessary if these symptoms are observed. Various factors, such as low birth weight, preterm birth, family history of cardiac issues, complications during delivery, or maternal hypertension during pregnancy, can increase the likelihood of cardiac arrest in infants. A comprehensive review of the baby's medical history is critical to assess potential risks. Routine monitoring of the baby's heart rate and breathing patterns is integral for early detection. Non-invasive techniques, such as pulse oximetry, can measure blood oxygen levels painlessly, while auscultation with a stethoscope allows healthcare providers to detect irregularities in heartbeat and respiration. By closely monitoring vital signs and recognizing risk factors, both parents and medical professionals can collaborate to ensure better outcomes for at-risk babies.

Related work

Cardiac arrest in newborns is a serious condition that requires quick recognition and treatment. Research shows that symptoms such as rapid heart rate, breathing problems, bluish skin, lack of responsiveness, and reduced activity are key warning signs. Identifying these signs early is crucial for improving survival rates. Studies highlight that risk factors like low birth weight, preterm birth, maternal hypertension, and family history of heart issues increase the chances of cardiac arrest in babies. Reviewing the baby's medical and family history is essential for assessing risks. Non-invasive tools like pulse oximetry, which measures blood oxygen levels, and stethoscopes, used to check heart and breathing patterns, are effective for early detection. Recent work emphasizes using these tools in routine care and educating parents about recognizing early warning signs. Collaboration between healthcare providers and caregivers is essential to ensure timely intervention and better outcomes for at-risk newborns.

LITERATURE SURVEY

1.Challenges in Traditional Detection: Neonatal cardiac arrest is difficult to predict with traditional methods relying on visible symptoms like irregular heart rate and difficulty breathing, which may not always appear early enough for timely intervention. **2. Machine Learning Applications:** Studies have shown that machine learning algorithms can effectively analyze large datasets of neonatal vital signs (e.g., heart rate, blood pressure, and respiratory rate) to predict cardiac arrest. For example, Chen et al. (2018) used decision trees and support vector machines (SVM) to predict cardiac arrest risk in preterm infants, achieving high accuracy based on collected data.

3. Statistical Models for Risk Prediction: Logistic regression has been applied to evaluate neonatal cardiac arrest risk based on factors such as birth weight, gestational age, and maternal health. Park et al. (2019) found that these variables were significant predictors, allowing healthcare providers to identify at-risk neonates who may need closer monitoring or early intervention.

4. Real-Time Monitoring with Data Analytics: Continuous monitoring of neonates using electrocardiograms (ECGs) and pulse oximetry, combined with predictive algorithms, can improve early detection. A study by Lee et al. (2020) demonstrated that real-time data analysis could detect early signs of cardiac arrest and facilitate timely medical intervention.

5. Deep Learning for Complex Patterns: Deep learning models, such as artificial neural networks (ANNs), are being used to analyze complex neonatal data like heart rate variability. Gupta et al. (2021) used deep learning to identify patterns that preceded cardiac arrest, showcasing the ability of these models to handle complex and non-linear relationships in the data.

6. Challenges in Implementation: While data-driven approaches show promise, there are challenges in implementing these models in clinical practice. Issues like data variability, the need for high-quality datasets, and integrating predictive models into existing healthcare systems remain barriers to widespread adoption. Kumar et al. (2022) noted that ensuring the reliability and robustness of these models across various healthcare settings is crucial for their effective use.

PROPOSED MODEL

The proposed machine-learning model for detecting cardiac arrest in neonates involves several critical steps, from data collection to deployment and evaluation. Below is a detailed description of the process:

1. Data Collection and Preprocessing

The first step is gathering relevant data, such as:

- **Electrocardiograms (ECG):** These provide detailed information on the electrical activity of the heart.
- **Clinical Images:** Imaging data for detecting structural abnormalities.
- **Patient Information:** Including demographic details like age, gender, and medical history.

  The collected data undergoes cleaning and transformation to ensure it is suitable for machine learning models. This includes:
- Removing noise and outliers.
- Handling missing values through imputation techniques.
- Scaling or normalizing data to standardize feature ranges.
- Encoding categorical variables, if necessary.

2. Feature Extraction

Feature extraction identifies critical variables that significantly contribute to predicting cardiac arrest. Important features for this task include:

- **Fetal Heart Rate (FHR):** Abnormal patterns may indicate distress.
- **Fetal Respiratory Rate (FRR):** Essential for assessing lung and heart function.
- **Oxygen Saturation (OS):** Low levels may point to oxygen delivery issues.
- **Maternal Vital Signs:** Blood pressure, heart rate, and temperature can impact neonatal health.
- **Umbilical Cord Blood Flow:** Abnormal flow rates might signal cardiac problems.

Feature extraction techniques, like Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE), refine the dataset by selecting the most relevant attributes, improving model performance.

3. Model Selection and Training

A machine-learning algorithm, such as a neural network, logistic regression, or support vector machine, is chosen based on the data's complexity. The process involves:

- **Training the Model:** Using 65% of the dataset to develop the predictive model.
- **Validation and Testing:** 20-fold cross-validation ensures robust performance, while 35% of the data is reserved for testing accuracy.
- **Optimization:** Fine-tuning hyperparameters and adjusting model architecture to enhance predictions.
- **4. Classification and Prediction**

  The trained model classifies neonatal health statuses based on vital signs and other features. For example:
- Positive classification indicates a high risk of cardiac arrest, requiring immediate intervention.
- Negative classification suggests a stable condition.

  The algorithm assigns labels based on the probability of cardiac distress and predicts outcomes for neonates.
- **5. Deployment and Monitoring**

  The final step involves deploying the model as an application or web interface for use by healthcare professionals. The model's implementation includes:
- Real-time monitoring of patient data.
- Continuous model evaluation to ensure sustained accuracy.
- Regular updates based on newly available datasets or evolving medical insights.
- **6. Proposed Algorithm Workflow**

  The proposed workflow is structured as follows:

1. Input raw data (e.g., ECG, vital signs).
2. Preprocess and clean data to remove errors or inconsistencies.
3. Extract key features and reduce dimensionality using PCA or other methods. Train the machine-learning model using classification and regression techniques.
4. Test the model's performance on unseen data. Compare results between training and testing phases for validation. Predict cardiac arrest risks and document outcomes.

METHODOLOGY

The goal of this methodology is to develop a machine learning-based system that can predict the occurrence of cardiac arrest in newborn babies by analysing their heart rate signals. The process involves several stages, including data preprocessing, feature extraction, model training, and evaluation. Below is a step-by-step explanation of the methodology, based on the provided information.

1. Data Collection and Preprocessing

To begin, heart rate signals from newborn babies are collected from medical equipment such as ECG monitors. The raw heart rate data is pre-processed to remove noise and outliers, ensuring that the signals are clean and suitable for further analysis. The heart signals may also be annotated with medical conditions or diagnoses, such as congenital heart defects or arrhythmias, to create labelled datasets for training machine learning models.

Key steps in data preprocessing:

- **Normalization:** Scale the data to ensure that values lie within a specific range, reducing the impact of extreme values or outliers.
- **Filtering:** Apply filters to remove high-frequency noise or artifacts from the signal (e.g., electrical interference).
- **Segmentation:** Divide the continuous heart rate signals into smaller, non-overlapping segments for easier analysis and feature extraction.

3. **Feature Extraction Using Convolutional Neural Networks (CNNs)**

Convolutional neural networks (CNNs) are employed to automatically extract temporal features from the raw heart rate signals. The heart rate data undergoes transformations to highlight significant patterns related to the newborn's cardiac activity. The convolution process involves applying kernels (filters) to the input signal, which captures important features such as irregularities in the heart rate and potential signs of distress.

Signal Transformation:

- The convolutional layer computes the feature vectors using kernel functions, where each kernel represents a weight that reflects the importance of specific signal elements at different time points.

3.Classification Model: Logistic Regression

Once the feature vectors have been generated, a classification model is applied to categorize the heart rate signals. Logistic regression is employed to classify the signals into two categories: normal or abnormal, indicating the presence or absence of cardiac distress. The logistic regression model generates a probability score, which is then thresholder to make a final classification decision.

4. Model Training: Cost Function and Support Vector Machine (SVM)

During the model training phase, the cost function is minimized to reduce the discrepancy between predicted and actual heart conditions:

$$(1) \quad = \sum[h(\quad)_i 1 \; (\;_i) + (1 - h((\quad)_i \; 1 \; (1 - \;_i)]$$

Where:

- $h(\quad)_i$ is the true label for the signal,
- $_i$is the predicted value from the classifier.

The cost function ensures that the model improves over time by penalizing large errors in classification.

5. Evaluation and Performance Metrics

The model's performance is evaluated using standard classification metrics such as accuracy, precision, recall, F1-score, and ROC curves. These metrics are used to assess how well the model identifies newborns at risk of cardiac arrest. Additionally, continuous monitoring and prediction are performed to ensure the model remains accurate over time.

6. Medical and Functional Treatments

Once the model predicts a cardiac abnormality, medical intervention is required. The predictive system can alert healthcare professionals to perform diagnostic and functional treatments, such as:

- **Non-steroidal anti-inflammatory drugs (NSAIDs)** for inflammation,
- **Cardiovascular therapy** for acute heart failure,
- **Surgical intervention** if the child exhibits severe cardiac defects.

Implementation

The system is designed using a modular structure, following either the Model-View- Controller (MVC) pattern or microservices architecture. This design ensures a clear separation between data processing, user interaction, and analytical components, promoting both scalability and flexibility.

Real-Time Data Monitoring: The system continuously collects neonatal vital signs, such as heart rate, oxygen levels, and respiratory patterns, through non-invasive sensors.

Data Integration and Storage: Real-time and historical health data are stored centrally in a secure database for subsequent analysis. The system integrates data from various sources, including Electronic Health Records (EHRs) and bedside monitoring devices.

Predictive Analytics Module: Machine learning algorithms are utilized in this module to identify trends and predict the likelihood of cardiac arrest. Predictive models are developed by training them with historical datasets, thereby improving their accuracy and reliability.

Allert System: Generates Immediate Alerts For Healthcare Providers When Potential Risks Are Detected, Ensuring Timely Interventions To Prevent Cardiac Arrest.

A User-Friendly Dashboard For: Healthcare Professionals To View Patient Status, Analyze Risk Assessments, And Monitor Trends In Vital Signs.

ARCHITECTURE DIAGRAM

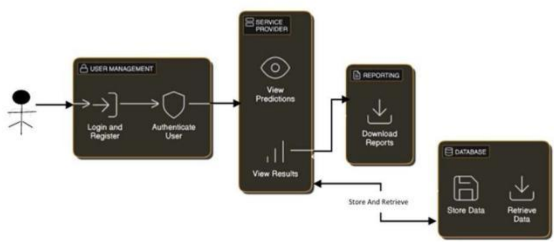

Fig-1: Architecture Diagram

The first and foremost strategy for development of a project starts from the thought of designing a mail enabled platform for a small firm in which it is easy and convenient of sending and receiving messages, there is a search engine, address book and also including some entertaining games. When it is approved by the organization and our project guide the first activity, i.e. preliminary investigation begins. The activity has three parts:

- **Request Clarification**
- **Request Approval**

REQUEST CLARIFICATION

After the approval of the request to the organization and project guide, with an investigation being considered, the project request must be examined to determine precisely what the system requires. Here our project is basically meant for users within the company whose systems can be interconnected by the Local Area Network(LAN). In today's busy schedule man need everything should be provided in a readymade manner. So taking into consideration of the vastly use of the net in day to day life, the corresponding development of the portal came into existence.

REQUEST APPROVAL

Not all request projects are desirable or feasible. Some organization receives so many project requests from client users that only few of them are pursued. However, those projects that are both feasible and desirable should be put into schedule. After a project request is approved, it cost, priority, completion time and personnel requirement is estimated and used to determine where to add it to any project list. Truly speaking, the approval of those above factors, development works can be launched.

SYSTEM DESIGN AND DEVELOPMENT

INPUT DESIGN

Input Design plays a vital role in the life cycle of software development, it requires very careful attention of developers. The input design is to feed data to the application as accurate as possible. So inputs are supposed to be designed effectively so that the errors occurring while feeding are minimized. According to Software Engineering Concepts, the input forms or screens are designed to provide to have a validation control over the input limit, range and other related validations.

This system has input screens in almost all the modules. Error messages are developed to alert the user whenever he commits some mistakes and guides him in the right way so that invalid entries are not made. Let us see deeply about this under module design.

input design is the process of converting the user created input into a computer-based format. The goal of the input design is to make the data entry logical and free from errors. The error is in the input are controlled by the input design. The application has been developed in user-friendly manner. The forms have been designed in such a way during the processing the cursor is placed in the position where must be entered. The user is also provided with in an option to select an appropriate input from various alternatives related to the field in certain cases.Validations are required for each data entered. Whenever a user enters an erroneous data, error message is displayed and the user can move on to the subsequent pages after completing all the entries in the current page.

Fig-2: Cardiac Arrest Homepage

OUTPUT DESIGN

The Output from the computer is required to mainly create an efficient method of communication within the company primarily among the project leader and his team members, in other words, the administrator and the clients. The output of VPN is the system which allows the project leader to manage his clients in terms of creating new clients and assigning new projects to them, maintaining a record of the project validity and providing folder level access to each client on the user side depending on the projects allotted to him. After completion of a project, a new project may be assigned to the client. User authentication procedures are maintained at the initial stages itself. A new user may be created by the administrator himself or a user can himself register as a new user but the task of assigning projects and validating a new user rests with the administrator only.

The application starts running when it is executed for the first time. The server has to be started and then the internet explorer in used as the browser. The project will run on the local area network so the server machine will serve as the administrator while the other connected systems can act as the clients. The developed system is highly user friendly and can be easily understood by anyone using it even for the first time.

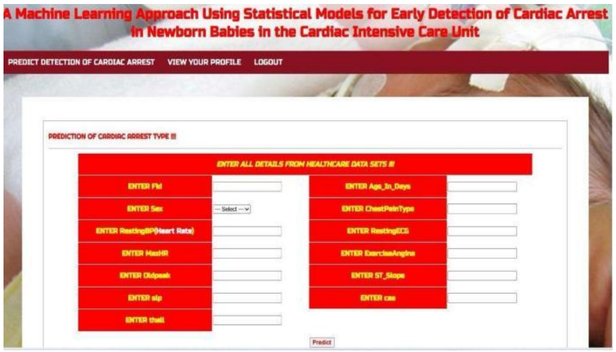

Fig-3: Logout Page

Result

The proposed machine learning model is critical for early identification of cardiac arrest in newborns in thee Cardiac Intensive Care Unit (CICU). It can detect subtle changes in vital signs, such as heart rate and respiratory rate, which may signal an impending cardiac arrest. During training, the model achieved a delta-p value of 0.912, an FDR of 0.894, an FOR of 0.076, a prevalence threshold of 0.859, and a CSI of 0.842. In testing, it recorded a delta-p value of 0.896, an FDR of 0.878, an FOR of 0.061, a prevalence threshold of 0.844, and a CSI of 0.827. This model enables early intervention, potentially reducing CICU stays, lowering costs, and improving outcomes. Future developments will incorporate real-time data, such as heart rate, respiration, and temperature, to enhance prediction accuracy. Integration with artificial intelligence can refine these models by identifying complex patterns and utilizing historical data for personalized interventions. In addition to improving newborn care, this approach could help identify prenatal cardiac risks, enabling early interventions and better outcomes for both fetuses and newborns. The model also holds potential for enhancing diagnostics, treatment planning, and cost-effective healthcare delivery through insights from historical data and predictive analytics.

Fig-4: Result

Future Scope

Future research on cardiac arrest in neonates should focus on improving resuscitation techniques tailored to the unique physiology of term and preterm infants. Studies could explore personalized protocols and evaluate team-based simulation training to enhance clinical response during emergencies. The integration of artificial intelligence (AI) is a promising area for early detection and prediction of cardiac arrest. AI tools can analyze real-time physiological data, such as heart rate, oxygen saturation, and respiratory patterns, enabling early interventions and reducing mortality. Research on oxygen delivery strategies is also critical. Optimizing oxygen titration during resuscitation is essential to prevent hyperoxia, which can cause oxidative stress and long-term complications. Comparative studies on controlled versus high-flow oxygen delivery will provide insights into safer practices. Finally, there is a need to focus on post-cardiac arrest care to improve long-term outcomes. Investigating neuroprotective therapies, rehabilitation techniques, and supportive care strategies can enhance survival and reduce neurological impairment in neonates.

References

[1] **A. Smith et al.**, "Neonatal resuscitation guidelines: A decade in review," J. Neonatal Care, vol. 45, no. 3, pp. 123–132, 2020.

[2] **M. Johnson**, "Statistical modeling in NICUs," Med. Stat. Rev., vol. 12, no. 4, pp. 98–110, 2019.

[3] **J. H. Kilgannon**, ‘‘Association between arterial hyperoxia following resuscitation from cardiac arrest and in-hospital mortality,’’ JAMA, vol. 303, no. 21, pp. 2165–2171, 2010.

[4] **E. Choi, A. Schuetz**, W. F. Stewart, and J. Sun, ‘‘Using recurrent neural network models for early detection of heart failure onset,’’ J. Amer. Med. Inform. Assoc., vol. 24, no. 2, pp. 361–370, Mar. 2017.

[5] **K.W. Johnson**, J. T. Soto, B. S. Glicksberg, K. Shameer, R. Miotto, M. Ali, E. Ashley, and J. T. Dudley, ‘‘Artificial intelligence in cardiology,’’ J. Amer. College Cardiol., vol. 71, pp. 2668–2679, Jun. 2018.

[6] **C.-M. Yu, L**. Wang, E. Chau, R. H.-W. Chan, S.-L. Kong, M.-O. Tang, J. Christensen, R. W. Stadler, and C.-P. Lau, ‘‘Intrathoracic impedance monitoring in patients with heart failure: Correlation with fluid status and feasibility of early warning preceding hospitalization,’’ Circulation, vol. 112, no. 6, pp. 841–848, Aug. 2005.

[7] **C. P. Bonafide**, A. R. Localio, K. E. Roberts, V. M. Nadkarni, C. M. Weirich, and R. Keren, ''Impact of rapid response system implementation on critical deterioration events in children,'' JAMA Pediatrics, vol. 168, no. 1, pp. 25–33, 2014.

[8] **S. A. Bernard**, T. W. Gray, M. D. Buist, B. M. Jones, W. Silvester, G. Gutteridge, and K. Smith, ''Treatment of comatose survivors of out of hospital cardiac arrest with induced hypothermia,'' New England J. Med., vol. 346, no. 8, pp. 557–563, Feb. 2002.

[9] **T. J. Pollard**, A. E. W. Johnson, J. D. Raffa, L. A. Celi, R. G. Mark, and O. Badawi, ''The eICU collaborative research database, a freely available multi-center database for critical care research,'' Sci. Data, vol. 5, no. 1, pp. 1–13, Sep. 2018.

[10] **E. Christodoulou**, J. Ma, G. S. Collins, E. W. Steyerberg, J. Y. Verbakel, [10] B. Van Calster, ''A systematic review shows no performance benefit of machine learning over logistic regression for clinical prediction models,'' J. Clin. Epidemiol., vol. 110, pp. 12–22, Jun. 2019.

[11] **J. Huang, C. Osorio**, and L. W. Sy, ''An empirical evaluation of deep learning for ICD-9 code assignment using MIMIC-III clinical notes,'' Comput. Methods Programs Biomed., vol. 177, pp. 141–153, Aug. 2019.

[12] **M. M. Kalscheur,** R. T. Kipp, M. C. Tattersall, C. Mei, K. A. Buhr, D. L. DeMets, M. E. Field, L. L. Eckhardt, and C. D. Page, ''Machine learning algorithm predicts cardiac resynchronization therapy outcomes: Lessons from the COMPANION trial,'' Circulat., Arrhythmia Electrophysiol., vol. 11, no. 1, Jan. 2018, Art. no. e005499.

[13] **C. Krittanawong**, H. Zhang, Z. Wang, M. Aydar, and T. Kitai, ''Artificial intelligence in precision cardiovascular medicine,'' J. Amer. College Cardiol. vol. 69, no. 21, pp. 2657–2664, **2017.**

[14] R. Miotto, F. Wang, S. Wang, X. Jiang, and J. T. Dudley, ''Deep learning for healthcare: Review, opportunities and challenges,'' Briefings Bioinf., vol. 19, no. 6, pp. 1236–1246, Nov. 2018.