Machine Learning Based Prediction Of Cardiac Arrest In Newborn Babies

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- Received Date: 11 Feb 2026
- Accepted Date: 02 Apr 2026
- Publication Date: 25 Apr 2026

Keywords

Cardiac Arrest Prediction, Early Detection, Machine Learning, Newborn-Health, Statistical Models

Abstract

Cardiac arrest in newborn babies is a life-threatening medical emergency that requires early detection and prompt treatment to reduce mortality and long-term health complications. Traditional monitoring methods used in neonatal intensive care units mainly rely on manual observation and basic clinical indicators, which often fail to identify subtle and early changes in a baby's vital signs, leading to delayed diagnosis and reduced survival chances. To overcome these limitations, the developed model proposes a machine learning–based system using statistical models for the early detection of cardiac arrest in newborn babies. The proposed system analyzes key physiological parameters such as heart rate, respiratory rate, oxygen saturation, and medical history data to identify early warning signs and potential risk factors. Machine learning techniques including Logistic Regression and Support Vector Machines are applied to detect hidden patterns that are difficult to recognize using conventional methods. The system enables automated, accurate, and continuous monitoring in the Cardiac Intensive Care Unit (CICU), supporting early clinical decision-making and timely medical intervention. By reducing reliance on manual monitoring, improving prediction accuracy, and minimizing response time, the proposed approach enhances the quality of neonatal care and increases the chances of survival for newborn babies through intelligent, data-driven healthcare solutions.

Introduction

ICardiac arrest in newborn babies is a devastating event that can lead to severe complications and death. Early detection of this condition is critical to provide the best care for these infants and ensure their long-term health. To ensure early detection, it is essential to understand the signs and symptoms associated with this condition and the risk factors that may put a baby at increased risk of cardiac arrest. The most common signs and symptoms of cardiac arrest in newborn babies are rapid heart rate and difficulty breathing. Other signs include a bluish tinge to the baby's skin, unresponsiveness, or decreased movement. If any of these signs are present, it is essential to seek medical attention immediately. Risk factors include low birth weight, family history of cardiac arrest, preterm birth, difficult delivery, or a mother with a history of high blood pressure during pregnancy. A baby's medical history should also be evaluated for any potential risks. To ensure early detection, regular monitoring of the baby's heart rate and respiratory rate is essential. Auscultation, or listening to the baby's heart rate and breathing with a stethoscope, can also help detect irregularities in heart rate or breathing. By understanding the signs and symptoms and being aware of risk factors, parents and medical professionals can work together to improve outcomes for these babies.

Cardiac arrest in newborns is a life-threatening medical condition that requires immediate medical attention. Early detection and intervention can improve outcomes and reduce mortality rates. Early detection has been difficult due to the complexity of the condition. Conventional monitoring methods may miss subtle changes in vital signs such as heart rate, respiratory rate, and oxygen saturation that are difficult to detect with the naked eye. These limitations can delay timely intervention and worsen outcomes. This project framework begins with the systematic collection of newborn patient data from medical records, including birth weight, gestational age, gender, vital signs, and other clinical and demographic information, which is then preprocessed through cleaning, normalization, feature selection, and encoding. On this prepared dataset, statistical and machine learning models such as Logistic Regression, Naive Bayes, Support Vector Machine, and Artificial Neural Networks are developed and validated to predict the likelihood of cardiac arrest in newborns and identify high-risk infants. These models detect subtle changes in vital signs that are difficult to spot with conventional monitoring.

Citation: Raju G, Sugur SK, Reddy STK, Thota HVR, Kancherla SP. Machine Learning Based Prediction Of Cardiac Arrest In Newborn Babies. GJEIIR. 2026;6(4):247.

RELATED WORK

Several research studies have focused on improving early detection of cardiac arrest and other critical conditions in newborn babies using advanced technologies. Traditional clinical scoring systems and manual monitoring methods have been widely used in neonatal intensive care units (NICU). However, these approaches mainly depend on human observation and predefined thresholds, which may not effectively detect subtle physiological changes in real time. With the advancement of artificial intelligence in the medical field, predictive modeling has gained significant attention for improving diagnostic precision. Various supervised learning methods, including Logistic Regression, Decision Trees, Support Vector Machines, and Neural Networks, have been implemented to examine clinical measurements and patient records. These approaches assist in discovering complex relationships among health indicators that are difficult to interpret through traditional analysis. A number of studies have concentrated on evaluating continuous physiological measurements such as pulse rate, breathing frequency, blood pressure, and oxygen levels to forecast emergency events in intensive care environments. Integrating data-driven analytics with continuous patient monitoring systems has demonstrated superior performance over rule-based alert mechanisms, allowing healthcare professionals to respond more quickly to critical situations. Advanced deep learning frameworks have also been investigated for processing extensive neonatal datasets, especially time-dependent medical signals. Models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are capable of extracting intricate temporal features from health data. Despite delivering strong predictive outcomes, these methods often demand substantial computational infrastructure and large volumes of training data, which may limit their implementation in certain clinical settings. In relation to our project, several prior works have specifically examined the use of Logistic Regression and Support Vector Machines for anticipating cardiac-related complications in newborn infants. These studies analyzed essential parameters such as heart rate variability, respiratory patterns, and oxygen saturation to determine risk probability. Their findings indicate that machine learning–based prediction can reveal warning signs before noticeable clinical deterioration occurs. Furthermore, real-time analytical systems deployed in Cardiac Intensive Care Units (CICU) have been designed to automatically interpret incoming patient information and produce early risk notifications. Compared to manual supervision, such intelligent systems significantly decrease reaction time and support more informed therapeutic decisions, aligning closely with the objectives of our proposed solution. Additionally, research combining historical medical background with live physiological measurements has shown improved classification performance. By merging demographic information, previous health conditions, and ongoing vital readings, predictive frameworks achieved higher reliability in identifying vulnerable newborns. This integrated approach directly supports our project's aim of developing an accurate, automated, and data-driven system for early cardiac arrest detection in neonatal care.

PROPOSED SYSTEM

Constructing the proposed cardiac machine-learning model requires several steps. First, the data must be collected and pre-processed. It includes gathering relevant cardiac data such a selector cardiograms (ECG), other medical images,and any relevant patient information, such as age and gender. The data must then be cleaned and transformed into a format suit able for machine learning algorithms, such as numerical or categorical values. Once the data is ready, a machine-learning model must be selected. It is typically a neural network model, as it can handle the complex relationships between the various data points. The model must then be trained using the data and evaluated for accuracy. If necessary, the model can be tweaked to improve its performance. Finally, the model must be deployed. It involves creating an application or web interface for the model to be used by medical professionals.

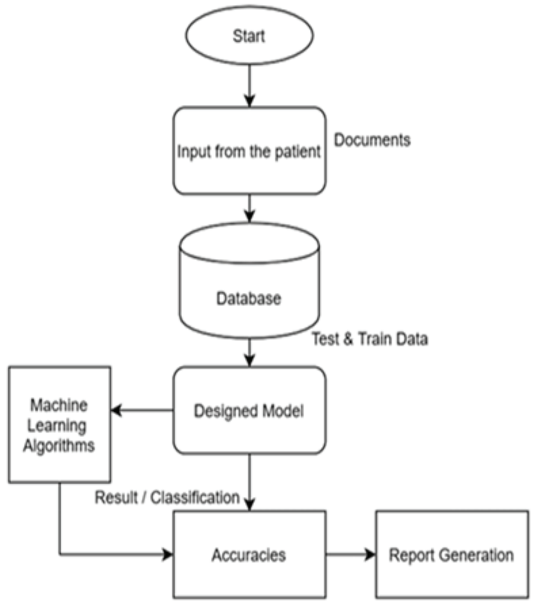

FIGURE 1. Proposed block diagram.

The model should also be continuously monitored for accuracy and necessary adjustments. The block diagram of the proposed machine learning model has shown in the following f ig.1, In the proposed method, the first detected patient symptoms are given as input. All these data are stored in the database, and their volumes are categorized. These classifications provide information regarding the treatment provided in the standard unit and the treatment provided in the emergency unit, depending on the severity of the illness. The proposed algorithm tests these provided information blocks to predict the severity of the patient's heart block problem. Accurate results are obtained, and treatments are provided for him. It is documented and stored back in the database. Cardiac Machine Learning model (CMLM) enables the detection and analysis of heart disease via a combination of several advanced machine-learning algorithms. At its core, CML involves creating a model which takes in large amounts of data, such as patient records, electrocardiogram (ECG) readings, clinical images of the heart, and other criteria and processes it to detect and predict cardiac abnormalities. The core components of a typical CML model consist of fea ture extraction, data pre-processing and model building. The Feature Extraction step converts raw data into meaningful information or features, which a machine learning model can use for further analysis. Feature extraction uses pre-trained algorithms to categorize data points and extract traits that may be essential features in a learning model. The critical features depend on the problem domain; for example, the data may contain patient records, ECGs, and clinical images of the heart for heart disease detection. The model can be better fitted to perform accurate data analysis by extracting essential features from these data points. Data pre-processing is a critical part of any machine learning model. It is responsible for cleaning and preparing data for further processing by removing or replacing any noise or outliers. It helps the model focus on the essential features and improves accuracy and efficiency. In the case of CML models, it is essential to prepare the data for input by removing or replacing any missing values and normalizing the data in order to detect any abnormalities in the data accurately. Once the data has been prepared, a model can be built using cardiac machine learning algorithm. With this algorithm, the model can classify the data and detect abnormalities, providing an accurate analysis of the data points, which can then be used for further medical diagnosis or treatment. The core components of a CML model allow for the detection of cardiac abnormalities efficiently and accurately. Combining feature extraction, data pre-processing, and model building, CML models can detect and predict heart conditions quickly and accurately, making them a valuable tool for medical professionals.

Symptoms Dataset

Data construction and modeling are as follows:

- A total of 84972 samples were selected from the data pcap files for the Newborn Babies in the Cardiac Intensive Care Unit . These samples contains fetal heart rate (FHR), oxygen saturation (OS), fetal respira tory rate (FRR), body temperature readings, and other medical constraints
- Totally 65% of data used for training (TR) the models and 35% of data used for testing (TS) the model
- It also used cross-validation on the training dataset with 20-folds.

Preprocessing

Preprocessing is an essential step in the machine learning approach for Early Detection of Cardiac Arrest in Newborn Babies in the Cardiac Intensive Care Unit. During this stage, the data are prepared for machine learning analysis. This includes cleaning and normalizing the data, selecting the appropriate features, and applying various transformations to the data. Additionally, any missing values or outliers must be identified and addressed. This process ensures that the data is suitable for machine learning algorithms. The data must be split into training, validation, and test sets so that the models can be evaluated and compared.

The preprocessing functions would likely include:

- Data cleaning: Remove any duplicate or irrelevant data, fill in missing values, and standardize data formats.
- Missing value imputation: Replace any missing values with meaningful estimates such as the mean of the feature or a prediction from another model.
- Data scaling: Scale the data so that all features have a similar range of values. This can be done using a variety of techniques such as min-max scaling or standardization.
- Feature selection: Select only the most relevant features that will help the model make accurate predictions. This can be done using techniques such as Recursive Feature Elimination or Principal Component Analysis.
- Data transformation: Transform the data into a format that the machine learning model can interpret. This can include one-hot encoding categorical features or applying a logarithmic transformation to skewed features. Preprocessing functions are necessary in order to clean and prepare the data for a machine learning model. Preprocessing functions can include data cleaning, missing value imputation, data scaling, feature selection, data transformation, and more.

Feature Extraction

Feature extraction for Early Detection of Cardiac Arrest in Newborn Babies is the process of identifying the most important features from the data that can be used to predict cardiac arrest in newborn babies. This is done by analyzing the patient's medical history, vital signs, and other relevant data. These features can be extracted from the data using various methods such as statistical analysis, machine learning algorithms, and feature selection techniques.

Feature extraction for a machine learning approach for early detection of cardiac arrest in newborn babies can involve the following:

- Fetal Heart Rate (FHR): The FHR can be used to mea sure the health of the baby. Abnormal FHR patterns can be an indication of cardiac arrest.
- Fetal Movements: A decrease or lack of fetal movements can be a sign of cardiac arrest and can be monitored for early detection.
- Maternal Vital Signs: Maternal vital signs such as blood pressure, heart rate, oxygen saturation, and temperature can be used to indicate the health of the baby. Abnormalities in these vital signs can be an indication of cardiac arrest. • Umbilical Cord Blood Flow: The umbilical cord blood flowrate can be used to measure the baby's oxygenation levels. Any abnormalities in the blood flow rate can be a sign of cardiac arrest. • Ultrasound: Ultra sound images can be used to detectany abnormalities in the baby's heart and can be used for early detection of cardiac arrest. These features can be used by the proposed machine learning algorithms to detect signs of cardiac arrest in newborn babies. For example, a machine learning approach for this task may involve using supervised learning techniques such as decision trees and logistic regression to identify the most important features from the data. This will help to identify the features that are predictive of the risk of cardiac arrest in newborn babies. Furthermore, feature selection techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) can be used to further refine the feature set and reduce the number of features required for the predictive model. Once the important features have been identified, they can be used to build a predictive model which can be used to help predict the risk of cardiac arrest in newborn babies. This model can then be used by healthcare providers to take preventative measures to reduce the risk of cardiac arrest in newborn babies

Classification

Classification is a supervised learning technique used in machine learning for early detection of cardiac arrest in new born babies. This technique is used to assign a label to a given input data based on its characteristics. In this case, the input data consists of the baby's vital signs such as heart rate, respiratory rate, body temperature, oxygen saturation, and other medical parameters. The classification algorithm will then analyze these parameters and output a label that indicates whether the baby is at risk of developing cardiac arrest or not. The output label can be either positive or negative, depend ing on the probability of the occurrence of the condition. The classification operation of a machine learning approach for Early Detection of Cardiac

Arrest in Newborn Babies involves several steps. First, a dataset is collected containing information about newborns and their vital signs. This dataset is then split into two sets: a training set and a testing set. The training set is used to train a machine learning model using supervised learning algorithms such as support vector machine and random forest. The model is then tested on the testing set to determine its accuracy. The model is evaluated on unseen data to assess its performance. This performance is then used as the basis for making decisions about whether or not a newborn is at risk for cardiac arrest. It can be used to identify patterns in the data and accurately classify them into the correct category.

Conclusion And Future Work

The deployment and evaluation of the Newborn Cardiac Arrest Prediction System demonstrate significant improvements in early risk identification, monitoring efficiency, and clinical decision support within neonatal intensive care units. The machine learning models, including Logistic Regression and Support Vector Machines, successfully analyzed vital parameters such as heart rate, respiratory rate, and oxygen saturation to accurately predict potential cardiac arrest risk. The system reduced manual monitoring effort and enabled faster identification of high-risk cases, supporting timely medical intervention. The system keeps newborn medical data safe by using secure login and protected database storage. Only authorized doctors and staff can access patient details. The medical dashboard is simple and easy to use, allowing healthcare professionals to view vital signs, prediction results, and alerts clearly in real time. Testing results showed that the system works smoothly and gives accurate predictions under continuous monitoring conditions. Performance measures like accuracy and recall confirmed that the model can correctly identify high-risk cases. Overall, the system meets the required objectives and can effectively support early detection of cardiac arrest in newborn babies. Finally, these models could be used to develop personalized interventions for individual patients, allowing for more effective treatments. Enhancing the proposed machine learning algorithm could also pave the way for predicting potential complications in fetuses or newborns. A healthcare team can determine risk levels for specific cardiac abnormalities before a baby is even born, which helps provide better interventions during the prenatal period. In addition, the proposed machine learning algorithm could be used to improve diagnostics and treatments. By study ing historical patient data, diagnostics can be improved, and doctors can be presented with more accurate and up-to date information when diagnosing a patient. It can lead to earlier interventions, better patient outcomes, and more cost effective treatments.

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