PREDICTIVE ANALYTICS FOR CARDIAC ARREST IDENTIFICATION IN NEONATES WITH MACHINE LEARNING FRAMEWORK

[1]Dandu Jaya Deep Varma, [2]Gali Anudeep Reddy,
[3]Ganji Naveen Kumar, [4]Thoutam Rathan, [5]B. Geeta Kumari
[1,2,3,4]B.Tech., Gokaraju Rangaraju Institute of Engineering and Technology, Kukatpally, Hyderabad, Telangana, India
[5]Assistant Professor, Gokaraju Rangaraju Institute of Engineering and Technology, Kukatpally, Hyderabad, Telangana, India
Email ID's: [1]jayadeep2256@gmail.com, [2]galianudeep111@gmail.com, [3]ganjinaveen12345@gmail.com, [4]rathansai4444@gmail.com, [5]geetha.bapr07@gmail.com

ABSTRACT: Diagnosis and prediction of heart related diseases requires more precision, perfection, and correctness because a little mistake can cause fatigue problem or death of the person, there are numerous death cases related to heart and their counting is increasing exponentially day by day. There is an essential need for a prediction system for awareness about detecting heart diseases at the early stages. Existing systems predict heart diseases in early stages using statistical models. Our proposed model will focus on using real-time data to identify cardiac arrest in the early stages. In our project, we calculate accuracy of machine learning algorithms for predicting heart disease with more accuracy.
Keywords: predict heart diseases, cardiac arrest, machine learning

I. INTRODUCTION

Cardiac 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. In order to ensure the early detection of cardiac arrest in newborn babies, it is essential to understand the signs and symptoms associated with this condition and the risk factors that may put a baby at an increased risk of cardiac arrest.

The most common signs and symptoms of cardiac arrest in newborn babies are a rapid heart rate and difficulty breathing. Other signs that may indicate a baby is in cardiac arrest 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 that may increase the likelihood of cardiac arrest in newborn babies include low birth weight, a family history of cardiac arrest, preterm birth, a 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. In order to ensure early detection of cardiac arrest in newborn babies, regular monitoring of the baby's heart rate and respiratory rate is essential. It can be done through pulse oximetry, a noninvasive, painless procedure that measures the amount of oxygen in the baby's blood.

Additionally, auscultation, or listening to the baby's heart rate and breathing with a stethoscope, can also help to detect any irregularities in the baby's heart rate or breathing. Early detection of cardiac arrest in newborn babies is vital to provide the best care for these infants and ensure their long-term health. By understanding the signs and symptoms of this condition and being aware of the risk factors that may put a baby at an increased risk of cardiac arrest, parents and medical professionals can work together to ensure the best possible outcomes for these babies. The early detection of cardiac arrest in newborn babies can be achieved using Statistical Models. Statistical models are mathematical techniques used to analyze and draw conclusions from data. These models are powerful tools in the medical field, as they can help predict, diagnose, and treat certain diseases and conditions. One example of a statistical model used for the early detection of cardiac arrest in newborn babies is the Logistic Regression model. This model uses data collected from the baby's medical history, such as birth weight, gestational age, and gender, to create a predictive model to determine the likelihood of cardiac arrest. This model can help doctors identify those babies at risk and can help them decide whether to treat the baby with medication or perform surgery to correct the issue. Another model used for the early detection of cardiac arrest in newborn babies is the Naive Bayes model. This model uses a probabilistic approach to analyze data and identify patterns to make predictions. The model can identify high-risk babies and help doctors determine the best course of action to take. The Support Vector Machine model is another statistical model used for the early detection of cardiac arrest in newborn babies. This model uses data collected from the baby's medical history and other sources to create a predictive model that can determine the likelihood of cardiac arrest. This model can identify those babies at risk and help doctors decide on the best course of treatment. Statistical models are powerful tools that can be used for the early detection of cardiac arrest in newborn babies. These models can help doctors identify those at risk so that they can provide the best possible treatment for the baby. Furthermore, these models can help doctors determine the best course of action to take in order to prevent or reduce the likelihood of cardiac arrest. Cardiac arrest in newborns is a life-threatening medical condition that requires immediate medical attention.

Early detection and intervention can improve the outcomes of these infants and reduce mortality rates. Statistical models are powerful tools that can be used to identify risk factors and predict the likelihood of cardiac arrest. Logistic regression is one of the best statistical models for the early detection of cardiac arrest in newborns. This model allows researchers to quantify the relationship between risk factors and the probability of experiencing an arrest. It can be used to identify the most critical factors associated with cardiac arrests, such as gender, gestational age, and birth weight.

Logistic regression can also be used to calculate the odds ratio for each risk factor, which indicates how much more likely an infant is to experience an arrest if they have a particular risk factor. Another effective model for the early detection of cardiac arrest in newborns is a support vector machine (SVM). This model type is well-suited for binary classification tasks, such as classifying an infant as either healthy or having experienced a cardiac arrest. It can also be used to identify important risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest. Finally, artificial neural networks (ANNs) can also detect cardiac arrest in newborns. ANNs are powerful machine learning models that can learn complex patterns from data. These models can be used to identify risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest. Logistic regression, support vector machines, and artificial neural networks are all effective models for the early detection of cardiac arrest in newborns. These models can be used to identify the most critical risk factors associated with the condition and predict the likelihood of an infant experiencing an arrest. Therefore, these statistical models should be used to improve newborns' early detection and intervention of cardiac arrest.

II. LITERATURE SURVEY

Ketan Gupta, Nasmin Jiwani, Giovanni Pau and Mohammad Alibakhshikenari et. al. [1] Statistical modeling techniques, such as logistic regression and support vector machines, were used to construct predictive models for cardiac arrest. The proposed model will be used in the CICU to enable early detection of cardiac arrest in newborn babies. In a training (Tr) comparison region, the proposed CMLA reached 0.912 delta-p value, 0.894 False discovery rate (FDR) value, 0.076 False omission rate (FOR) value, 0.859 prevalence threshold value and 0.842 CSI value. In a testing (Ts) comparison region, the proposed CMLA reached 0.896 delta-p values, 0.878 FDR value, 0.061 FOR value, 0.844 prevalence threshold values and 0.827 CSI value. It will help reduce the mortality and morbidity of newborn babies due to cardiac arrest in the CICU.

Prabu Pachiyannan, Musleh Alsulami, Deafallah Alsadie, Abdul Khader Jilani Saudagar ,Mohammed AlKhathami and Ramesh Chandra Poonia et. al. [2] By analyzing data from infants diagnosed with CHD, the model identifies key risk factors contributing to mortality. Armed with this knowledge, healthcare providers can devise customized interventions, including intensified care for high-risk infants and early detection and treatment strategies. The proposed diagnostic model utilizes maternal clinical history and fetal health information to accurately predict the condition of newborns affected by CHD. The results are highly promising, with the proposed Cardiac Deep Learning Model (CDLM) achieving remarkable performance metrics, including a sensitivity of 91.74%, specificity of 92.65%, positive predictive value of 90.85%, negative predictive value of 55.62%, and a miss rate of 91.03%. This research aims to make a significant impact by equipping healthcare professionals with powerful tools to combat CHD-related newborn mortality, ultimately saving lives and improving healthcare outcomes worldwide.

Hyeonhoon Lee, Hyun-Lim Yang, Ho Geol Ryu, Chul-Woo Jung, Youn Joung Cho, Soo Bin Yoon, Hyun-Kyu Yoon and Hyung-Chul Lee et. al. [3] Predicting in-hospital cardiac arrest in patients admitted to an intensive care unit (ICU) allows prompt interventions to improve patient outcomes. We developed and validated a machine learning-based real-time model for in-hospital cardiac arrest predictions using electrocardiogram (ECG)-based heart rate variability (HRV) measures. The HRV measures, including time/frequency domains and nonlinear measures, were calculated from 5 min epochs of ECG signals from ICU patients. A light gradient boosting machine (LGBM) algorithm was used to develop the proposed model for predicting in-hospital cardiac arrest within 0.5–24 h. The LGBM model using 33 HRV measures achieved an area under the receiver operating characteristic curve of 0.881 (95% CI: 0.875–0.887) and an area under the precision-recall curve of 0.104 (95% CI: 0.093–0.116). The most important feature was the baseline width of the triangular interpolation of the RR interval histogram. As our model uses only ECG data, it can be easily applied in clinical practice

Minsu Chae, Hyo-Wook Gil, Nam-Jun Cho and Hwamin Lee et. al. [4] We conducted early prediction research on cardiac arrest using time-series data such as biosignal and laboratory data. To derive the data attributes that affect the occurrence of cardiac arrest, we performed a correlation analysis between the occurrence of cardiac arrest and the biosignal data and laboratory data. To improve the positive predictive value and sensitivity of early cardiac arrest prediction, we evaluated the performance according to the length of the time series of measured biosignal data, laboratory data, and patient data range. We propose a machine learning and deep learning algorithm: the decision tree, random forest, logistic regression, long short-term memory (LSTM), gated recurrent unit (GRU) model, and the LSTM–GRU hybrid model. We evaluated cardiac arrest prediction models. In the case of our proposed LSTM model, the positive predictive value was 85.92% and the sensitivity was 89.70%.

Innocent Chukwudi Ekuma, Gideon Ihebuzo N Ndubuka, Taofik Oladimeji Azeez and Onyebuchi Nosiri et. al. [5] In this study, we developed Machine learning (ML) algorithms for the prediction of cardiac arrest. Our protocol employs different methods for classification of the HD dataset using univariate and Bivariate analysis for prediction of cardiac arrest on input data which contains 11 features such as ChestPainType, age, gender etc and Pair plot to check the distribution of each variable and how it correlated with the target variable (Cardiac Arrest). Our result indicated that the ASY pain type was the highest ChestPainType that had cardiac arrest with 54% while NAP had 22%, ATA had 19% and TA 5%. The male genders were also observed to have the highest rate of cardiac arrest when compared to the female genders. Our protocol was able to predict the occurrence of cardiac arrest and at the same time recommend possible treatments, medication and exercises regime to the patient via the web application interface.

Priscilla Yu, Michael Skinner, Ivie Esangbedo, Javier J. Lasa, Xilong Li, Sriraam Natarajan, and Lakshmi Raman et. al. [6] We collected demographic, laboratory, and vital sign information from the electronic health records (EHR) of all the patients that were admitted to a single-center pediatric cardiac intensive care unit (CICU), between 2010 and 2019, who had a cardiac arrest during their CICU admission, as well as a comparator group of randomly selected non-cardiac-arrest controls. We compared traditional logistic regression modeling against a novel adaptation of a machine learning algorithm (functional gradient boosting), using time series data to predict the risk of cardiac arrest. Results: A total of 160 unique cardiac arrest events were matched to non-cardiac-arrest time periods. Using 11 different variables (vital signs and laboratory values) from the EHR, our algorithm's peak performance for the prediction of cardiac arrest was at one hour prior to the cardiac arrest (AUROC of 0.85 [0.79,0.90]), a performance that was similar to our previously published multivariable logistic regression model. Conclusions: Our novel machine learning predictive algorithm, which was developed using retrospective data that were collected from the EHR and predicted cardiac arrest in the children that were admitted to a single-center pediatric cardiac intensive care unit, demonstrated a performance that was similar to that of a traditional logistic regression model. While these results are encouraging, future research, including prospective validations with multicenter data, is warranted prior to the implementation of this algorithm as a real-time clinical decision support tool.

Samuel Harford, Marina Del Rios, Sara Heinert, Joseph Weber, Eddie Markul, Katie

Tataris, Teri Campbell, Terry Vanden Hoek and Houshang Darabi et. al. [7] We utilized all (N = 2398) patients treated by the Chicago Fire Department Emergency Medical Services included in the Cardiac Arrest Registry to Enhance Survival (CARES) between 2013 and 2018 who survived to hospital admission to develop, test, and analyze ML models for decisions after return of spontaneous circulation (ROSC) and patient survival. ML classification models, including the Embedded Fully Convolutional Network (EFCN) model, were compared based on their ability to predict post-ROSC decisions and survival. The EFCN classification model achieved the best results across tested ML algorithms. The area under the receiver operating characteristic curve (AUROC) for CA and Survival were 0.908 and 0.896 respectively. Through cohort analyses, our model predicts that 18.3% (CI 16.4–20.2) of patients should receive a CA that did not originally, and 30.1% (CI 28.5–31.7) of these would experience improved survival outcomes. ML modeling effectively predicted hospital decisions and neurologic outcomes. ML modeling may serve as a quality improvement tool to inform system level OHCA policies and treatment protocols.

III. PROPOSED SYSTEM

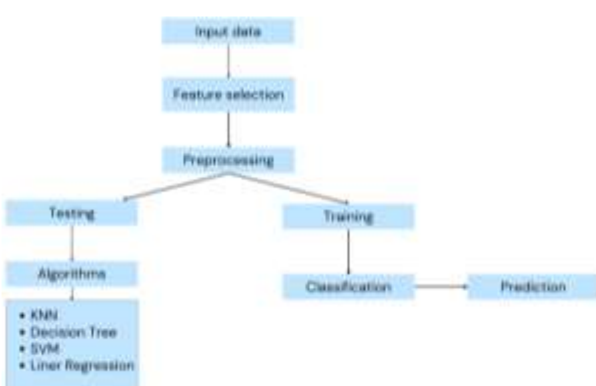

Fig. 1 Architecture

Acquired heart disease in a child develops for many reasons. This disease affects the heart valves, in which granulomas form in the stroma. In 75% of cases, rheumatic endocarditis is responsible for rheumatic development. Connective tissue diseases spread. Lupus erythematosus, scleroderma, dermatomyositis and other pathologies often cause kidney and heart problems. Any powerful blows to the chest area can cause the development of a defect. After operations already performed on the heart, for example, valvotomy, complications can trigger the defect's development. Atherosclerosis is a chronic disease of the arteries and blood vessels in which atherosclerotic plaques begin to form on their walls. Rarely, atherosclerosis also causes changes in the work and structure of the heart. This list shows that if a child develops a heart defect, the reasons for this are very diverse, but it is essential to at least detect them so that the prescribed treatment is efficient and more effective. The initial dataset used for conventional heart disease prediction contained a sample size of 407 patients and included 79 features. However, for the purpose of this study, the sample size was reduced to 369 patients. The study focused on nine specific features, which encompassed the monitored parameters relevant to heart disease prediction. These parameters included sex, blood pressure, resting electrocardiogram (ECG), maximum heart rate, birth weight, weight at 4 weeks, weight difference between birth and 4 weeks, blood oxygen saturation, and body temperature. In the dataset, systolic pressure is reduced, and diastolic pressure is normal or increased. With aortic insufficiency, there are no complaints during compensation; sometimes, tachycardia and a pulse behind the sternum are observed.

Different deep learning algorithms can be used for classification tasks, and the choice of the best algorithm depends on the nature of the data and the desired outcome. When it comes to predicting newborn mortality in CHD, popular algorithms include support vector machines, decision trees, and artificial neural networks. Congenital malformation with blockages refers to a condition where there are difficulties in adequately draining blood from the ventricles. This condition can be classified into different types: Stenosis: This occurs when the aorta narrows in the region of the valve. Aortic consolidation: This refers to pathology where the lumen in a specific area of the aorta is narrowed or completely closed. Pulmonary stenosis: This is a disorder in which the outflow tract of the right ventricle becomes narrow, obstructing blood flow into the pulmonary artery.

When choosing a deep learning algorithm for predicting newborn mortality in CHD, it is crucial to consider the specific data used for training and testing. For example, if the dataset is small, a more complex algorithm like support vector machines may not be necessary. Conversely, if the dataset is extensive or contains a significant amount of noise, a simpler algorithm such as a decision tree may struggle to learn the underlying patterns effectively. Additionally, the desired outcome of the classification plays a significant role. If the goal is to predict whether a newborn will die from CHD or not, a binary classification algorithm would suffice. However, if the aim is to predict the severity of the disease, a multi-class classification algorithm would be required. By carefully considering the dataset and desired outcome, one can compare different deep learning algorithms and select the most suitable one for the task.

IV. RESULTS

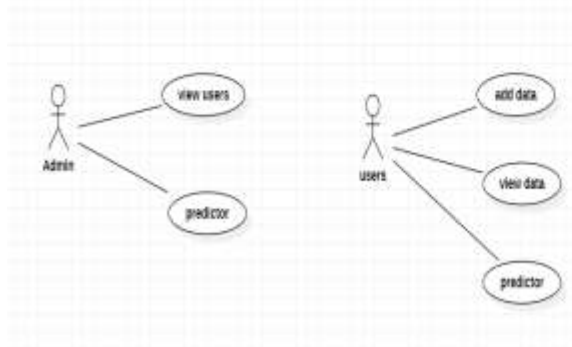

Fig. 2 Use case diagram

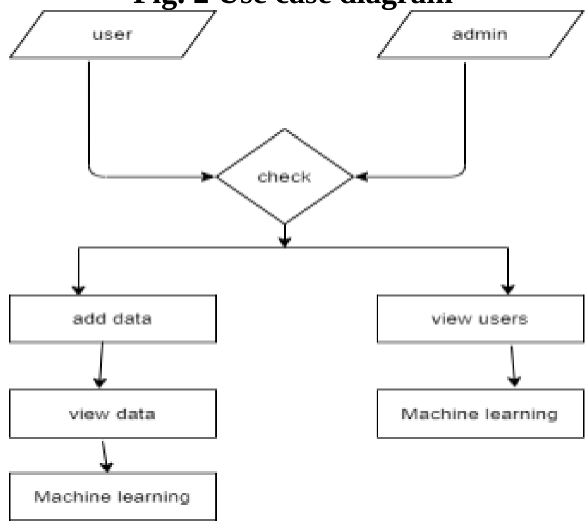

Fig. 3 Data flow diagram

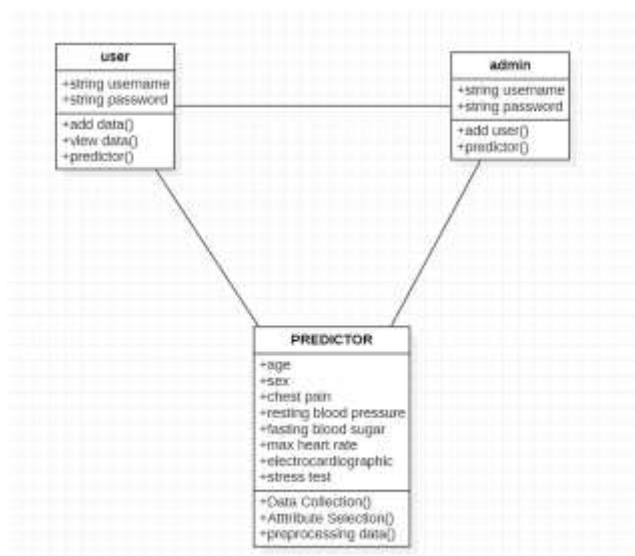

Fig. 4 Class diagram

V. CONCLUSION

The proposed machine learning model is crucial for early detection of cardiac arrest in newborns within the Cardiac Intensive Care Unit (CICU). This model efficiently identifies infants at high risk by accurately analyzing subtle changes in vital signs like heart and respiration rates. In the training comparison region (Tr), the proposed Cardiac Machine Learning Algorithm (CMLA) achieved notable values: 0.912 delta-p, 0.894 FDR, 0.076 FOR, 0.859 prevalence threshold, and 0.842 CSI. In the testing region (Ts), the CMLA yielded 0.896 delta-p, 0.878 FDR, 0.061 FOR, 0.844 prevalence threshold, and 0.827 CSI.

Implementing this model allows healthcare providers to intervene early, potentially preventing adverse outcomes and reducing CICU stay, thereby cutting costs and improving overall outcomes. Future improvements will focus on utilizing real-time data, incorporating various physiological measures, and employing artificial intelligence for more accurate predictions. These enhancements may include integrating data from diverse sources, such as medical histories, to personalize interventions.In future, Explore integration possibilities with existing healthcare systems and electronic health records (EHRs). This can enhance real-time monitoring and provide seamless communication between the predictive analytics tool and healthcare professionals. Establish a feedback loop for continuous improvement of the machine learning model. Expand the predictive analytics framework to include the prediction of other critical vital signs in neonates. This holistic approach can provide a comprehensive picture of the infant's health, aiding in early intervention for various medical conditions. Collaborate with NICUs to implement the predictive analytics tool in real-world settings.

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