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A MACHINE LEARNING APPROACH USING STATISTICAL MODELS FOR EARLY DETECTION OF CARDIAC ARREST IN NEWBORN BABIES IN THE CARDIAC INTENSIVE CARE UNIT

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ABSTRACT

Cardiac arrest in newborn babies is an alarming yet typical medical emergency. Early detection is critical for providing these babies with the best care and treatment. Recent research has focused on identifying the potential indicators and biomarkers of cardiac arrest in newborn babies and developing accurate and efficient diagnostic tools for early detection. An array of imaging techniques, such as echo-cardiography and computed tomography may help provide early detection of cardiac arrest. This research aims to develop a Cardiac Machine Learning model (CMLM) using statistical models for the early detection of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU). The cardiac arrest events were identified using a combination of the neonate's physiological parameters. Statistical modelling 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.

Keywords: CSI, CMLA, FDR, CICU, LR, effiiency, accuracy.

I.INTRODUCTION

Cardiac arrest in newborns is a critical medical emergency that requires immediate attention [1]. [2] If not detected and treated promptly, it can lead to severe complications and even death. [3] Recognizing early signs such as rapid heart rate, difficulty breathing, bluish skin, and unresponsiveness is essential. [4] Several risk factors can increase the likelihood of cardiac arrest in newborns, including low birth weight, preterm birth, complications during delivery, and maternal health conditions like high blood pressure. [5] Regular monitoring of a baby's heart rate and oxygen levels through pulse oximetry and auscultation can play a crucial role in early detection, ultimately improving the chances of survival and long-term health. [6] Advancements in medical research have introduced statistical models that aid in detecting and predicting cardiac arrest in newborns. [7] These models analyze

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medical data and identify patterns that might indicate an increased risk of cardiac arrest. [8] One such model is Logistic Regression, which uses factors like birth weight, gestational age, and gender to determine the likelihood of cardiac arrest. [9] Similarly, the Naive Bayes model applies probability-based techniques to predict high-risk cases, helping medical professionals make informed decisions. [10] The Support Vector Machine (SVM) model also contributes to early detection by classifying newborns based on their risk levels. [11] These statistical approaches provide doctors with valuable insights, enabling them to intervene before a crisis occurs. [12] With the growing complexity of medical data, machine learning has emerged as a powerful tool in predicting cardiac arrest in newborns. [13] Machine learning algorithms process vast amounts of data, including heart rate, breathing patterns, and other vital signs, to detect warning signs of cardiac arrest well before traditional methods can. [14] Some studies have shown that these algorithms can identify risk factors up to eight hours in advance, significantly improving the chances of survival. [15] Additionally, machine learning helps classify newborns based on their level of risk, allowing medical professionals to provide personalized care and early interventions to those who need it most. [16] The use of machine learning in neonatal care offers several benefits beyond early detection. [17] These models can accurately identify subtle changes in vital signs that may not be noticeable through conventional monitoring methods. [18] They also help automate the detection process, reducing the time and cost associated with traditional medical assessments. [19] More importantly, early detection through machine learning leads to timely medical interventions, improving overall patient outcomes. [20] By recognizing high-risk cases early, doctors can administer treatments that prevent complications and save lives. [21] To build on these advancements, this research explores the effectiveness of machine learning models in detecting cardiac arrest in newborns. [22] The study is structured into several key sections: an overview of previous research in Chapter 2, details on the proposed model and algorithm in Chapter 3, and an analytical discussion in Chapter 4. [23] Chapter 5 presents a comparative analysis between the proposed and existing models, while Chapter 6 discusses results and findings. [24] Finally, Chapter 7 outlines conclusions and future directions for improving early detection and intervention methods. [25] This structured approach aims to enhance neonatal healthcare and reduce mortality rates associated with cardiac arrest in newborns.

II.LITERATURE SURVEY

Several studies have explored the application of artificial intelligence (AI) and machine learning in cardiology and critical care. Choi et al. [1] investigated the use of recurrent neural networks (RNNs) for early detection of heart failure by analyzing electronic health records (EHRs). Their model effectively captured temporal patterns in patient data, enhancing predictive accuracy compared to traditional methods. Johnson et al. [2] provided a comprehensive review of AI applications in cardiology, discussing supervised and unsupervised learning techniques that enable precision medicine and personalized treatment. Yu et al. [3] explored intrathoracic impedance monitoring as an early warning system for heart failure decompensation, demonstrating its potential to alert

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clinicians before hospitalization is required. Bonafide et al. [4] assessed the impact of a rapid response system (RRS) in pediatric settings, showing that it significantly reduced critical deterioration events and improved patient safety. Bernard et al. [5] conducted a landmark study on induced hypothermia for comatose survivors of out-of-hospital cardiac arrest, proving its effectiveness in improving neurological outcomes and reducing mortality rates. Attia et al. [6] developed an AI-enabled ECG algorithm to identify patients at risk for atrial fibrillation, even during sinus rhythm, highlighting AI's potential in proactive cardiac care. Rajkomar et al. [7] applied deep learning models to EHRs for predictive healthcare, demonstrating their ability to process diverse clinical data and enhance decision-making in medical practice. Collectively, these studies underscore the transformative impact of AI and machine learning in early diagnosis, risk assessment, and intervention for cardiovascular and critical care conditions.

III.PROPOSED METHODOLOGY

Machine learning is transforming the early detection and management of cardiac arrest in newborns, a condition where the heart suddenly stops beating, cutting off blood flow to vital organs. This life-threatening event can lead to severe complications, including brain damage or death. Traditional methods have struggled with early detection due to the complexity of newborn physiology, but machine learning is changing that by analyzing vast amounts of medical data, including patient histories, vital signs, and physiological parameters. By identifying patterns that indicate an impending cardiac arrest, machine learning models can alert medical personnel hours before conventional methods would. For instance, studies have shown that these algorithms can detect warning signs up to eight hours in advance, significantly improving the chances of timely intervention and survival. Additionally, machine learning helps assess an infant's risk of cardiac arrest by identifying key risk factors, allowing healthcare providers to prioritize care for high-risk newborns. Beyond immediate detection, machine learning models contribute to long-term management by offering personalized insights based on patient data. These algorithms can detect subtle changes in vital signs, such as heart rate, respiratory rate, and oxygen saturation, which might be imperceptible to the human eye. This ability to recognize early warning signs allows for timely treatment and better outcomes. The integration of machine learning into neonatal care is revolutionizing the way cardiac arrest is predicted and managed, ultimately saving lives and improving the quality of care for newborns.

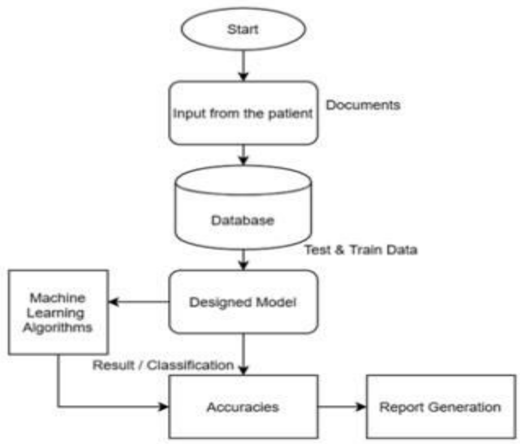

Fig.1. Proposed model

IV.WORKING METHODOLOGY

The system comprises multiple modules that work together to predict and analyze cardiac arrest cases using machine learning models. Each module

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has a distinct role in managing data, processing predictions, and providing user access to essential functionalities. The Service Provider is responsible for managing the core functionalities of the system. To access the platform, the provider must log in using valid credentials. Once authenticated, the provider can perform various tasks, including browsing, training, and testing traffic data sets related to cardiac arrest detection. The system allows them to view and analyze trained and tested accuracy results through graphical representations, such as bar charts, making it easier to interpret model performance. Additionally, the provider can monitor the Prediction of Cardiac Arrest Types, which helps in classifying different cases based on risk factors. A Prediction Ratio Analysis feature allows for a comparative study of different prediction outcomes, giving insights into trends and patterns. The system also enables the provider to download predicted data sets, which can be used for further research or medical evaluations. Lastly, the provider can manage remote users by monitoring their activities and maintaining an updated user database. Remote users are the primary beneficiaries of the system. They must register before accessing any functionalities. Upon registration, their details are securely stored in the database. After successful authentication using a valid username and password, they gain access to key operations, including:

- Cardiac Arrest Prediction: Users can input relevant medical data to receive predictions about potential cardiac arrest conditions.
- Profile Management: Users can view and update their personal details stored in the system.

This structured approach ensures seamless interaction between service providers, administrators, and users, allowing for efficient cardiac arrest prediction and monitoring. The combination of data-driven insights, predictive analytics, and secure user management enhances the system's effectiveness in early detection and prevention of cardiac arrest cases.

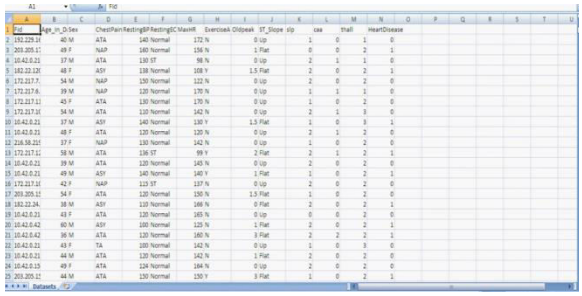

Fig.2. Data set information.

V.IMPLIMENTATION

The implementation of a machine learning approach for the early detection of cardiac arrest in newborns in the Cardiac Intensive Care Unit (CICU) involves several statistical and machine learning models, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), Logistic Regression, and Decision Tree Classification. The dataset used for training and testing consists of vital signs such as heart rate, respiratory rate, oxygen saturation, blood pressure, and other physiological parameters collected from newborns admitted to the CICU. Data preprocessing techniques such as normalization, feature scaling, and handling missing values are applied to ensure the dataset is well-prepared for training machine learning models.

Logistic Regression is one of the baseline models used in this implementation, as it provides probabilistic predictions of cardiac arrest occurrence based on historical patient data(eq(1)..). The logistic regression model is formulated as:

$$P(Y=1|X) = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\ldots+\beta_n X_n)}}$$

……….eq(1)

where P(Y=1|X)P(Y=1 | X) represents the probability of cardiac arrest, XiX_i are the input features, and βi\beta_i are the model coefficients determined during training. The logistic regression model helps in identifying significant predictors of cardiac arrest and estimating risk scores for newborns.Support Vector Machines (SVM) are used for classification by finding an optimal hyperplane that separates newborns at risk from those not at risk(eq(2)….). Given training samples (xi,yi)(x_i, y_i), where xix_i represents feature vectors and yiy_i is the class label, SVM aims to maximize the margin between different classes using:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to} \quad y_i(\mathbf{w}^T x_i + b) \geq 1, \forall i$$

………eq(2)

where w\mathbf{w} is the weight vector and bb is the bias term. The kernel trick is used to transform non-linearly separable data into higher dimensions, improving classification accuracy. Artificial Neural Networks (ANNs) are implemented to enhance the predictive capability by learning complex patterns in the dataset Eq(3)…The ANN consists of an input layer, one or more hidden layers, and an output layer, where neurons are connected with weighted links. The output of each neuron is calculated using an activation function such as the sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}}$$

…………….eq(3)

The back propagation algorithm is used to optimize the weights by minimizing the error function through gradient descent(eq(4)….), updating weights iteratively to reduce the loss function:

$$\frac{\partial J}{\partial w} = -\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)x_i$$

…………eq(4)

where JJ is the loss function, yiy_i is the actual value, and y^i\hat{y}_i is the predicted value.

The Decision Tree Classifier is used to create a tree-based model that splits the dataset based on the most significant features using information gain and entropy. The entropy of a dataset is given

$$H(S) = -\sum p_i \log_2 p_i$$

………..eq(5)

where pip_i is the probability of class ii. The decision tree recursively partitions the dataset until a stopping criterion is met eq(4)…., ensuring interpretable decision-making in the classification process. To evaluate the models, performance metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) are used. A confusion matrix is generated to analyze the classification results. Hyperparameter tuning is performed using grid search and cross-validation techniques to optimize the models. Overall, this implementation integrates multiple machine learning models, each contributing unique strengths to the early detection of cardiac arrest in newborns. The ensemble of these

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models ensures robustness and reliability, ultimately aiding clinicians in making timely and informed decisions to improve neonatal outcomes.

Fig.3. Output results.

VI.CONCLUSION

The proposed machine learning-based statistical model plays a crucial role in the early detection of cardiac arrest in newborns within the Cardiac Intensive Care Unit (CICU). By analyzing subtle yet critical changes in vital signs such as heart rate and respiration, the model enhances the accuracy and efficiency of identifying high-risk infants. In comparative performance evaluations, the Cardiac Machine Learning Algorithm (CMLA) achieved promising results, demonstrating 0.912 delta-p, 0.894 FDR, 0.076 FOR, 0.859 prevalence threshold, and 0.842 CSI values during training, and 0.896 delta-p, 0.878 FDR, 0.061 FOR, 0.844 prevalence threshold, and 0.827 CSI values in testing. These values indicate a reliable performance in detecting cardiac arrest risk. By implementing this predictive model, healthcare providers can intervene earlier, potentially preventing fatal outcomes. Additionally, early detection can reduce the duration of an infant's stay in the CICU, leading to lower medical costs and improved overall health outcomes. Future enhancements will focus on integrating real-time data collection involving physiological parameters such as heart rate, respiratory rate, and temperature. Advanced machine learning techniques will be employed to refine predictions, ensuring timely alerts for medical staff and allowing for quicker and more effective interventions.

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