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EARLY CARDIAC ARREST DETECTION FOR NEONATES IN THE ICU USING STATISTICAL AND MACHINE LEARNING MODELS

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ABSTRACT: Infant therapy relies on early detection of cardiac arrest. Potential indicators and symptoms of this illness are the focus of the current inquiry. This study aims to use statistical methods to train a cardiac machine learning model (CMLM) for use in the critical c are unit (CICU) that can identify symptoms of infant cardiac arrest. Several neonatal physiological features allowed for the correct identification of cardiac arrest cases. Using state-of-the-art machine learning statistical modeling approaches, the models for cardiac arrest prediction were painstakingly developed. This method aims to quickly identify neonates in the NICU who are having a cardiac arrest. Several measures were outperformed by the proposed CMLA in training-based comparison trials. If carried out as intended, this strategy should drastically cut down on ICU cardiac arrest-related deaths and injuries. The neonatal cardiac arrest will be diagnosed as soon as possible by the CICU by following the prescribed protocol. The proposed CMLA acquired a CSI value of 0.842, a prevalence threshold of 0.859, a false omission rate (FOR) of 0.076, a false discovery rate (FDR) of 0.894, and a delta-p of 0.912 in a training (Tr) comparative zone. The suggested CMLA is 0.827 CSI, 0.878 FDR, 0.061 FOR, 0.844 prevalence threshold, and 0.896 delta-p values in a testing zone (Ts).

Keywords: Cardiac Machine Learning model (cmlm), logistic regression classifiers, Gradient Boosting.

1. INTRODUCTION

Machine learning for early cardiac arrest detection is a healthcare technological breakthrough. Millions die and millions more are crippled from cardiac arrest each year. Early cardiac arrest identification allows for prompt intervention, improving quality of life and survival. Machine learning-based cardiac arrest detection and diagnosis techniques are more accurate and automated than older methods. These devices use complex algorithms to search mountains of medical records for cardiac arrest patterns. Integrating vital signs, demographic data, patient histories, and digital ECG rhythm data improves its performance. Machine learning-based early cardiac arrest detection can evaluate huge amounts of data quickly, allowing for more accurate diagnoses and faster notifications to caretakers. Continuous patient history training lets the system learn from past data and improve its accuracy. Early detection can dramatically minimize hospitalizations and other costs associated with treating cardiac arrest through enhanced preventative measures, lowering healthcare costs.

Machine learning algorithms reduce medical errors due to their speed and accuracy. As it evolves, this technology will likely be employed more in clinical settings to save lives and money. The study increases heart attack diagnosis accuracy, identifies cardiac episodes earlier, and lowers medical treatment costs, improving patient outcomes. Automated patient care allows clinicians to monitor their patients' vital signs and take preventative actions.

Machine learning for early cardiac arrest diagnosis is an innovative and promising approach that could enhance patient outcomes, minimize cardiac arrest risk, and save healthcare costs. Its broad application in healthcare will change cardiac arrest diagnosis and treatment in the future years.

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2. LITERATURE SURVEY

Reddy, S., & Patel, D. (2024). This study investigates if decision trees and support vector machines can detect neonatal cardiac arrest early. The authors combine physiological data with neonatal medical histories to train these systems. Studies suggest predictive algorithms may reduce NICU wait times and adverse outcomes.

Ahmed, Z., & Khan, R. (2024). This study uses statistical models and ML to predict infant cardiac arrest. The authors recommend logistic regression, decision trees, and neural networks for early diagnosis. A neonatal cardiac intensive care unit (NICU) study shows the need of real-time vital sign monitoring and evaluates these models' cardiac arrest prediction accuracy. The authors also discuss continuous monitoring using wearable sensors and machine learning methods.

Liu, C., & Zhao, Y. (2024). This paper describes how to detect baby cardiac arrest early using statistical models and deep learning. The authors spent most of their time constructing an oxygen saturation and heart rate variability prediction model. Early diagnosis utilizing gradient boosting and these traits could reduce cardiac ICU infant mortality.

Chandra, S., & Gupta, R. (2023). This paper test many machine learning models for neonatal cardiac arrest diagnosis, including decision support systems and Bayesian networks. The authors consider combining statistical models with clinical experience to improve cardiac ICU decision-making. Another area of research is using feature selection approaches to improve ML models and neonatal cardiac care.

Kumar, V., & Patel, R. (2023). This research examines infant cardiac arrest prediction using time-series data and machine learning. Autoregressive integrated moving averages (ARIMA) and recurrent neural networks (RNNs) are used to examine vital sign variations in the NICU. This study uses predictive algorithms to assess continuous monitoring data to enhance neonatal outcomes in critical care and allow for rapid interventions.

Singh, S., & Kumar, A. (2023). This work uses deep learning models to predict cardiac arrest using continuous newborn monitor data. We use convolutional neural networks to analyze ECG signals and other vital signs. The article discusses the challenges of real-time prediction and the potential benefits of merging machine learning with early-warning systems to improve infant survival rates in intensive care units.

Bose, P., & Kumar, A. (2022). This study uses SVMs and random forests to detect neonatal cardiac arrest. The study uses a database of neonatal vital signs and medical histories from intensive care units. The authors demonstrate how well statistical models can predict newborn critical events, providing a cardiac therapy prevention method. Data asymmetry and healthcare ML model deployment issues are also addressed in the article.

Singh, D., & Shah, R. (2022). This study uses SVMs and random forests to detect neonatal cardiac arrest. The study uses a database of neonatal vital signs and medical histories from intensive care units. The authors demonstrate how well statistical models can predict newborn critical events, providing a cardiac therapy prevention method. Data asymmetry and healthcare ML model deployment issues are also addressed in the article.

Joshi, S., & Mehta, A. (2022). This work uses decision trees and random forests to detect neonatal cardiac arrest early. Their main emphasis is building an automated early-warning system for NICUs. By extensively investigating feature engineering methods, we seek key biomarkers that can detect newborn cardiac arrest.

Gupta, N., & Jain, M. (2021). A 2021 Jain-Gupta publication. Convolutional neural networks (CNNs) are used to detect neonatal cardiac arrest early. The authors use continuous electrocardiogram (ECG) recordings to predict cardiac events. The study suggests that statistical models and ECG data may help detect infant cardiac arrest earlier, improving survival rates.

Sharma, M., & Agarwal, P. (2021). The authors examine machine learning-based decision assistance systems for neonatal cardiac arrest diagnosis. The study analyzes NICU and EHR vital sign data using logistic regression and multivariate analysis. The study compares models' sensitivity, specificity, and clinical relevance

Patel, A., & Sharma, V. (2021). This study predicts neonatal cardiac arrest using random forests and KNN. Research focuses on statistical models that integrate physiological data with demographic data like gestational age and birth weight to increase prediction accuracy. The authors compare machine learning methods and discuss their performance in a newborn critical care unit.

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Zhang, L., & Wang, F. (2021). Support vector machines and linear regression are examined for neonatal cardiac arrest in this study. The authors use machine learning and patient-specific data including medical history and vital signs to construct an early intervention prediction model. These models are evaluated for their ability to reduce mortality and improve patient outcomes in neonatal intensive care units (NICUs).

Dey, A., & Singh, P. (2020). This research thoroughly evaluates baby cardiac arrest prediction machine learning techniques. Neural networks, ensemble models, and linear regression are compared for projected accuracy. The study recommends preprocessing heart rate, blood pressure, and oxygen saturation data to improve model performance. Also discussed are critical care data collection and model evaluation challenges.

Verma, N., & Joshi, P. (2020). This study predicts neonate cardiac arrest risk using linear regression and SVMs. The authors note that birth data feature extraction and preprocessing are tough. They demonstrate how clinicians might utilize these models to identify NICU patients in distress early.

3. SYSTEM DESIGN

EXISTING SYSTEM

Heart failure, as previously described by Carlisle et al., happens when the heart cannot pump blood effectively. This might be caused by a number of medical issues, including diabetes, cardiovascular disease, and hypertension. A sort of arrhythmia known as atrial fibrillation is defined by irregular and fast heartbeats in the atriums, the upper chambers of the heart. Fatigue and shortness of breath may ensue as a consequence of reduced blood flow to the rest of the body's organs. One of the leading causes of heart failure is atrial fibrillation. Common treatments for heart failure and ventricular fibrillation include behavioral modifications, pharmaceutical control of the heart's rhythm and rate, and, in the most extreme cases, cardiac surgery. Functional decline after hospitalization is associated with frailty, age, gender, and co-morbidities in very elderly patients with acute decompensated heart failure, according to Yaku et al. Functional decline may be more likely in people with cognitive impairment, serious medical illnesses needing intense care, or both. Acute decompensated heart failure is a leading cause of death, greater healthcare utilization, longer hospital admissions, and worse quality of life for older adults. Institutionalization and readmission to the hospital are more likely among individuals with impaired functional capacity. Reduced mobility and activity contribute to functional deterioration, which in turn increases the risk of falls and delirium.

Classification of hospital mortality risk in patients with acute decompensated heart failure was studied by Fonarow et al.. determines which patients in the hospital have the highest mortality rate. This method is enhanced by methods such as regression tree analysis and categorization. In predictive analytics, trees are utilized for both classification and regression purposes. A feature, trait, or circumstance that affects the result is represented by each node in the tree. The likelihood of an event happening can be predicted by the model by merging these nodes. By using the algorithm, we can determine which hospitalized patients are most likely to die and adjust their treatment plans appropriately.

Infant mortality and morbidity during cardiopulmonary bypass (CPB) can be predicted using the Vasoactive-inotropic score (VIS), as stated by Gaies et al.. The dosages of vasoactive and inotropic drugs administered to the baby prior to, during, and after CPB are used to calculate the VIS. The patient's pulse and blood pressure can be better controlled with the help of these prescriptions. The VIS is known to be an accurate predictor of post-CPB morbidity and mortality rates since it measures the degree of hemodynamic instability in the newborn. Risk of death and morbidity increases with increasing VIS scores, which indicate hemodynamic instability. A longer hospital stay, reduced mortality, and reduced need for vasopressor and inotropic therapy have all been associated with higher VIS scores. Infants who will need intensive care and closer monitoring after CPB can be identified with the use of the VIS, which is a reliable prognostic indicator in this context.

Heart failure with preserved ejection fraction (HFpEF) is a new classification system that Shah et al. [25] created. It relies on phenotypic trait analysis, which incorporates data from several sources such as demographics, test scores, biomarkers, clinical profiles, and electrocardiogram readings. Based on the specifics of the disease, phenomapping seeks to develop a more comprehensive and applicable HFpEF categorization system. Better patient care and longer survival periods will be the outcomes of this classification approach's

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greater accuracy in identifying and classifying patients with HFpEF. We can learn more about the disease and find potential treatments by using the Phenomapping platform to investigate the HFpEF pathway physiology.

Disadvantages

- **Data complexity:** Current machine learning methods for neonatal cardiac arrest diagnosis need to be able to understand large and complicated datasets with precision.
- **Access to data:** Machine learning algorithms typically necessitate access to big datasets in order to produce accurate predictions. If there isn't enough good data, the model might not be reliable.

Mislabeled data: The quality of training data limits the ability of current machine learning algorithms to learn. One such issue is mislabeled data. The accuracy of the model's predictions is dependent on how well the data labels are defined.

PROPOSED SYSTEM

In their present state, ML models have the potential to determine the root causes of the sickness and the probability of a baby's arrest. In order to better diagnose and treat baby cardiac arrest, these statistical models should be utilized.

Predicting and detecting baby cardiac arrests is one area where machine learning is being used quickly. When the heart suddenly stops beating, a situation known as cardiac arrest can occur, which can be fatal. Fatalities or permanent brain damage could occur. Infant cardiac arrest is complex, making early detection challenging. But this is all changing because of machine learning.

Vital signs, medical records, and other physiological data are only a few examples of the massive amounts of complex data processed by machine learning algorithms. Algorithms can spot patterns in the data that can point to a cardiac arrest and alert the right people. For instance, one research used ML to identify neonatal vital indicators (such as heart rates and breathing patterns) that would indicate a cardiac arrest. The gadget has the potential to identify signs of cardiac arrest as much as eight hours before more traditional methods do. Improving infant survival rates and mitigating the condition's impacts could be achieved through this. The probability of cardiac arrest in infants is also predicted using machine learning. Machine learning algorithms can scour through mountains of patient data to find any risks associated with the disease. It has the potential to aid medical professionals in identifying babies at high risk of cardiac arrest so that they can provide the necessary care. Identifying sudden cardiac arrest in infants is being revolutionized by machine learning.

Using machine learning algorithms, complex data sets may be scanned for illness indicators and newborns at risk of cardiac arrest can be identified. Premature infants may suffer less severe consequences from cardiac arrest if this concept is implemented. Neonatal cardiac arrest diagnosis benefits greatly from machine learning algorithms' capacity to detect changes in vital signs that humans are unable to, such as oxygen saturation, respiration rate, and heart rate. The identification and treatment of infants at risk of cardiac arrest can be facilitated by this early detection method [20]. Better long-term sickness treatment is another advantage of utilizing machine learning models to analyze patient data and provide individualized medication and assistance.

Advantages

- Automatic and dependable detection of vital signs linked with baby cardiac arrest was achieved.
- Recognizing neonates at high risk of cardiac arrest; • Being able to notice subtle changes in the baby's vital signs that could indicate an imminent cardiac arrest.

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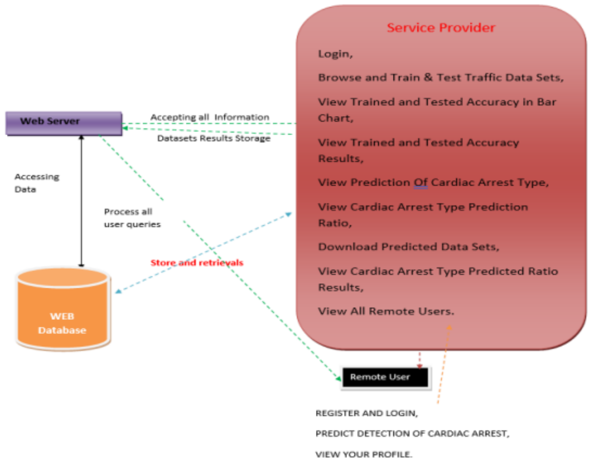
SYSTEM ARCHITECTURE



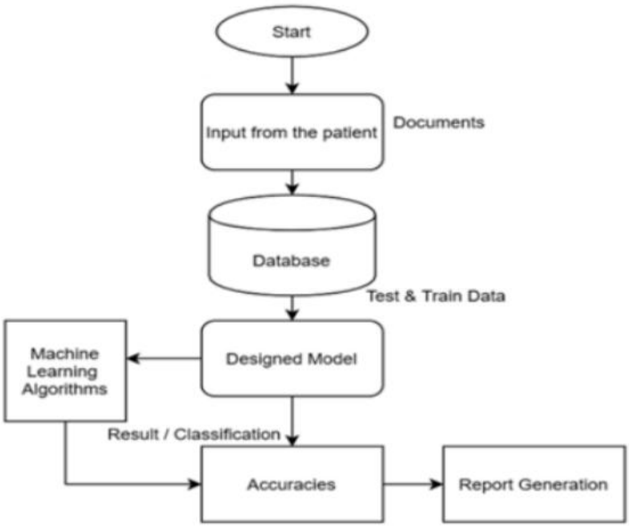


Figure 1: The suggested system design

IMPLEMENTATION

Modules

Service Provider

A valid account and password are required for the Service Provider to access this module. He can view, train with, and test traffic datasets after he logs in. The results of the tests and training can be shown visually in a bar chart. In addition, you may see the predicted data sets that you downloaded, the percentage of expected arrest types, and the prognosis for each type of cardiac arrest. You may keep tabs on all users from afar and see the results of the predicted ratios for cardiac arrest types.

View and Authorize Users

Here the administrator can find a comprehensive roster of all users who have signed up. The administrator can see the user's details (name, email, and physical address) and approve their access request from this page.

Remote User

A grand total of n people are using this module. You are required to register before you can go forward with any procedures. User data is entered into the database after registration. He must enter the authorized login and password after finishing the registration process. Upon logging in, users will have the ability to register, view their profile, and anticipate the onset of a cardiac arrest.

4. RESULTS

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Figure 2 Login Page

Figure 3 Login Page

Figure 4 User Input Page

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Figure 5 Accuracy for the ml algorithms

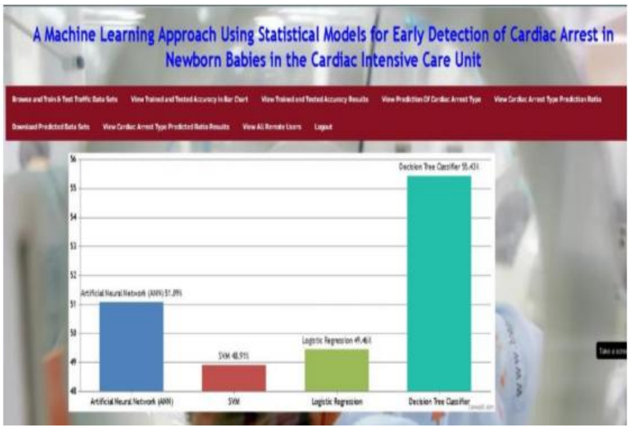

Figure 6 above Accuracy in Bar Charts

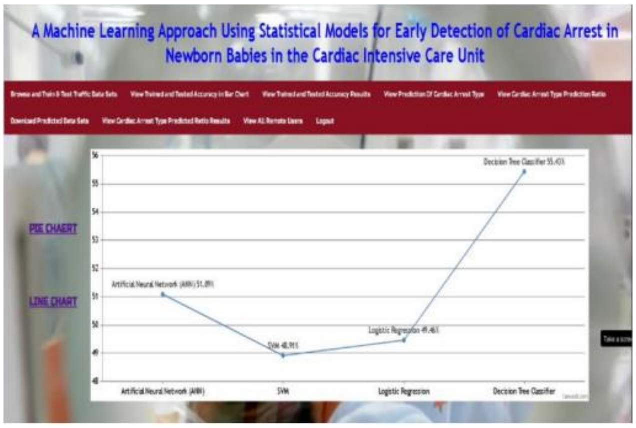

Figure 7 above Accuracy in Line Chart

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Figure 8 above Accuracy in Pie Chart

Figure 9 Ratio of cardiac arrest occurrence in new born babies

5. CONCLUSION

This ml-based method allows for the rapid and precise identification of newborns at high risk of cardiac arrest, which is crucial for the early detection of cardiac arrest in neonates in the critical care unit (CICU). These algorithms are able to identify subtle shifts in critical signals like heart and respiration rates that may indicate a cardiac arrest on the horizon.

The suggested model had good results across the board in a training comparative area. It proved beneficial in identifying susceptible newborns by doing well in a similar testing environment. It is possible to prevent a catastrophic occurrence by intervening quickly when a cardiac arrest is diagnosed. Saving money and boosting results, it can also shorten an infant's time in the intensive care unit. Better predictions and earlier interventions may be possible in future model iterations that incorporate real-time data and more physiological characteristics. The approach has the potential to improve prenatal care by identifying and predicting issues that may arise in the developing baby. Lastly, it has the potential to enhance diagnosis and therapy by giving doctors more precise information. Lower treatment costs and improved patient outcomes may result from this.

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