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Paper Authors

Mrs.Bethapudi ArunaSri,Y. Mouna,S. Akshitha,V. Samhitha



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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

¹Mrs.Bethapudi ArunaSri, ²Y. Mouna, ³S. Akshitha, ⁴V. Samhitha

¹Assistant Professor, ^{2,3,4}Students

Department Of CSE

Malla Reddy Engineering College for Women

ABSTRACT

A frightening yet common medical emergency is cardiac arrest in infants who have just been delivered. The greatest care and therapy for these infants can only be provided if detected early. Recent studies have aimed to create reliable diagnostic techniques for early diagnosis of neonatal cardiac arrest by finding possible biomarkers and indications of this condition. Echocardiography, computed tomography, and other imaging modalities may aid in the early diagnosis of cardiac arrest. In order to identify cardiac arrest in newborn newborns in the Cardiac Intensive Care Unit (CICU) early on, this project seeks to construct a Cardiac Machine Learning model (CMLM) utilizing statistical methods. Multiple neonate physiological characteristics were used to identify the cardiac arrest occurrences. Predictive models for cardiac arrest were constructed using statistical modeling approaches, including logistic regression and support vector machines. The suggested methodology will be used in the CICU to facilitate the early identification of neonatal cardiac arrest. With a training (Tr) comparison area, the suggested CMLA achieved a delta-p value of 0.912, an FDR value of 0.894, an OR value of 0.076, a prevalence threshold value of 0.859, and a CSI value of 0.842. The suggested CMLA

achieved test-specific values of 0.896 for delta-p, 0.878 for FDR, 0.061 for FOR, 0.844 for prevalence threshold, and 0.827 for CSI in a testing (Ts) comparison range. Babies induced cardiac arrest in the neonatal intensive care unit will have a lower risk of death and morbidity as a result.

1. INTRODUCTION

Babies experiencing cardiac arrest for the first time are tragically vulnerable to life-threatening consequences or even death. In order to provide these babies the finest treatment possible and guarantee their long-term health, early diagnosis of this illness is important. Knowing the symptoms of cardiac arrest in newborns and the variables that can enhance a baby's risk of cardiac arrest is crucial for early diagnosis of this disease [1]. Newborns often have trouble breathing and a racing heart as indications of cardiac arrest. A blue tint to the skin, inresponsiveness, or reduced movement are further symptoms that might point to a newborn experiencing cardiac arrest. Get medical help right once if you notice any of these symptoms. Low birth weight, a history of cardiac arrest in the family, premature delivery, complications during delivery, or a mother's hypertension throughout pregnancy are some of the risk factors that may raise the chance of cardiac arrest in newborns [2].

Additionally, any possible dangers should be assessed by reviewing the baby's medical history. Monitoring the heart rate and breathing rate of a newborn infant on a regular basis is crucial for the early diagnosis of cardiac arrest. One painless and noninvasive method is pulse oximetry, which detects the oxygen levels in the baby's blood [3]. It is also possible to identify abnormalities in the baby's breathing and heart rate by auscultation, which involves listening to these sounds with a stethoscope. Infants experiencing a cardiac arrest during delivery must be identified promptly so that they may get optimal treatment and have the greatest chance of a long and healthy life. Medical providers and parents may collaborate for the benefit of these infants by learning to recognize the symptoms of this disease and the variables that raise the likelihood of cardiac arrest [4]. It is possible to use statistical models to identify cardiac arrest in newborns at an early stage. Mathematical tools for data analysis and inference are statistical models. Because of their usefulness in illness prediction, diagnosis, and treatment, these models are becoming indispensable in medicine [5]. Early diagnosis of cardiac arrest in newborn neonates is made possible, for instance, by using statistical models such as the Logistic Regression model. In order to forecast the probability of cardiac arrest, this model incorporates information gathered from the baby's medical record, including birth weight, gestational age, and gender [6]. Doctors may use this model to find at-risk pregnancies and choose the best course of treatment, whether it medication or surgery, for the infant. The Naive Bayes model is

another tool for identifying sudden cardiac arrest in infants as soon as possible [7]. To generate predictions, this model examines data using a probabilistic technique, looking for trends. The model may help clinicians choose the optimal course of action by identifying newborns at danger [8]. One other statistical model that may identify sudden cardiac arrest in infants is the Support Vector Machine model. In order to forecast the possibility of cardiac arrest, our model incorporates information gathered from the baby's medical record and other sources [9]. Doctors may use this model to determine the optimal course of therapy for at-risk infants. One of the most effective ways to identify sudden cardiac arrest in infants is with the use of statistical models [10]. In order to provide the greatest care for the newborn, these models may assist physicians identify individuals who are at danger. Medical professionals may also use these models to figure out how to lessen the chances of cardiac arrest [11].

Babies experiencing cardiac arrest need urgent medical treatment since it is a potentially fatal medical emergency. These babies' outcomes and death rates may be improved with early identification and care. When it comes to predicting the probability of cardiac arrest and identifying risk variables, statistical models are effective tools [12]. When it comes to statistical models for infant cardiac arrest identification, logistic regression is among the best. Using this model, scientists can put a number on how certain variables affect the likelihood of an arrest [13]. Important variables linked to cardiac arrests, including gender, gestational age, and birth weight,

may be determined using this method [14]. Another application of logistic regression is to determine the odds ratio for each risk factor; this will show the relative importance of each risk factor in determining the likelihood that a newborn will have an arrest. Support vector machines (SVMs) are another powerful model for infant cardiac arrest early detection [15]. Classifying a newborn as healthy or having had a cardiac arrest are two examples of binary classification tasks that this model type excels at. Predicting the probability of a baby having a cardiac arrest and identifying critical risk variables linked with arrest are two further possible uses [16]. The last capability of artificial neural networks (ANNs) is the detection of infant cardiac arrest. Machine learning models using ANNs' strength is in their ability to learn intricate patterns from data. Predicting the probability of a cardiac arrest in a newborn and identifying risk variables linked with arrest are both possible applications of these models. Successful models for the early diagnosis of neonatal cardiac arrest include logistic regression, support vector machines, and artificial neural networks. Using these models, we may determine which characteristics are most important for the disease and how likely it is that a newborn will have an arrest. As a result, these statistical models have to be used to enhance the early identification and intervention of cardiac arrest in infants [17]. Predicting and detecting neonatal cardiac arrest using machine learning is becoming more common. When the heart abruptly stops pumping blood, it causes a potentially fatal condition known as cardiac arrest. Death or

long-term brain damage may result. Newborn cardiac arrest has been difficult to diagnose early on because of the condition's intricacy. But that is all changing thanks to machine learning [18]. Medical records, vital signs, and other physiological data are examples of the kinds of complicated data that machine learning algorithms go through in vast quantities. The algorithms can identify data patterns that might indicate a cardiac arrest and notify the appropriate authorities. As an example, one research analyzed the vital signs of neonates, including heart rates, breathing patterns, and more, in order to apply machine learning to identify indicators of cardiac arrest. Signs of cardiac arrest might be recognized by the algorithm as much as eight hours before traditional techniques could. Newborns' odds of survival and the severity of the condition's effects might both be greatly enhanced by this. The likelihood of cardiac arrest in infants is also anticipated with the use of machine learning. Machine learning algorithms can investigate the illness's potential dangers by poring over mountains of patient data. It may aid doctors in determining which infants are most likely to have a cardiac arrest and getting them the treatment they need.

2. LITERATURE SURVEY

The use of AI in cardiovascular medicine, Machine learning and artificial intelligence are going to change the world in a lot of ways, and cardiology is no different. This study aims to educate physicians on important facets of AI and ML, discusses some of the current uses of these approaches in cardiology, and suggests future ways that cardiovascular care may use AI. First, the

article provides a brief overview of predictive modeling ideas that are applicable to cardiology, including feature selection and common mistakes such incorrect dichotomization. The second part of the article goes over some of the most popular supervised learning algorithms and how they have been used to cardiology and other fields. Finally, it explains how these methods could be used to enable precision cardiology and improve patient outcomes. It starts by describing the advent of deep learning and related methods, which are collectively called unsupervised learning. It then gives contextual examples in general medicine and cardiovascular medicine.

"Correlation with fluid status and feasibility of early warning preceding hospitalization: Intrathoracic impedance monitoring in patients with heart failure,"

Fluid overload often leads to hospitalization for patients with heart failure. Consequently, it is preferable to have a dependable system in place for continuously checking the fluid state. For the purpose of detecting possible fluid overload before to heart failure admission and to ascertain the association between intrathoracic impedance and conventional measurements of fluid status when hospitalized, we assessed an implanted device that could monitor intrathoracic impedance. A left pectoral area pacemaker and a right ventricular defibrillation lead were implanted in 33 individuals with NYHA class III and IV heart failure. Between the lead and the pacemaker casing, intraathoracic impedance was routinely monitored and documented. Patients' hydration status and pulmonary capillary wedge pressure were tracked throughout

their hospital stays. Fluid overload was the reason for ten patients' 25 hospitalizations spanning 20.7 $\pm$ 8.4 months. On average, intraathoracic impedance dropped 12.3 $\pm$ 5.3% ($P<0.001$) during 18.3 $\pm$ 10.1 days prior to each hospitalization. The decrease in impedance started 15.3 $\pm$ 10.6 days ($P<0.001$) before to the start of symptoms that were becoming worse. While in the hospital, there was a negative relationship between intrathoracic impedance and both pulmonary capillary wedge pressure ($r=-0.61$, $P<0.001$) and net fluid loss ($r=-0.70$, $P<0.001$). There were 1.5 false-positive (threshold crossing without hospitalization) detections per patient-year of follow-up when using automated detection of impedance declines to identify fluid overload hospitalizations; the sensitivity was 76.9%. Prior to the start of patient symptoms or hospitalization for fluid overload, intraathoracic impedance decreases, and it is inversely connected to pulmonary capillary wedge pressure and fluid balance. If measured regularly, impedance may serve as a diagnostic tool for titrating medicine and an early warning system for approaching decompensation.

"Induced hypothermia as a treatment for comatose survivors of cardiac arrests that occur outside of hospitals,"

The prognosis is not good for cardiac arrests that occur outside of hospitals. While hypothermia administered soon after spontaneous circulation restoration has been shown to enhance neurologic outcome in animal research, no such trials have been conducted in people. For patients who did not regain consciousness during resuscitation following an out-of-hospital

cardiac arrest, we conducted a randomized controlled experiment to evaluate the effects of normothermia with mild hypothermia. The 77 patients who participated in the trial were randomly randomized to either normothermia or hypothermia, which is defined as a core body temperature reduction of 33 degrees Celsius within 2 hours after spontaneous circulation returns and maintenance of that temperature for 12 hours. Survival until hospital release with adequate enough neurologic function to be discharged to home or a rehabilitation center was the major end measure. The patient demographics in the hypothermia and normothermia groups were comparable. When comparing the outcomes of patients treated with hypothermia and normothermia, we found that twenty-one patients (or 49 percent) survived and had a favorable result (i.e., were released home or to a rehabilitation center) compared to nine patients (or 26 percent, $P=0.046$) treated with normothermia. Hypothermia had a 5.25 (95% CI, 1.47 to 18.76; $P=0.011$) odds ratio for a positive outcome compared to normothermia after adjusting for baseline differences in age and time from collapse to the resumption of spontaneous circulation. Cardiac index, systemic vascular resistance, and hyperglycemia were all negatively correlated with hypothermia. On the other hand, the incidence of side effects was the same. Based on our first findings, it seems that mild hypothermia therapy improves outcomes for patients in coma after resuscitation from cardiac arrest that occurred outside of a hospital.

3. EXISTING SYSTEM

As previously mentioned by Carlisle et al. [21], when the heart is unable to pump blood effectively, a condition known as heart failure sets up. Numerous medical issues might lead to this, such as diabetes, coronary artery disease, and hypertension. The top chambers of the heart, known as the atriums, pulse quickly and erratically in atrial fibrillation, a kind of arrhythmia. This may reduce the volume of blood that is pumped to the rest of the body, which can produce symptoms like weariness and shortness of breath. One of the most prevalent causes of heart failure is atrial fibrillation. Treatment for heart failure and atrial fibrillation often include pharmacological management of the heart's rhythm and pace, behavioral modifications, and, in extreme cases, cardiac surgery.

Frailty, age, gender, and co-morbidities are risk factors for functional deterioration after hospitalization in very elderly patients with acute decompensated heart failure, as reviewed by Yaku et al. [22]. The likelihood of functional decline may also rise in the context of cognitive impairment, severe medical conditions requiring rigorous treatment, or both. Longer hospital stays, more healthcare usage, death, and worse quality of life are clinical outcomes linked to functional deterioration in elderly patients with acute decompensated heart failure. There is a correlation between functional deterioration and an increase in the likelihood of institutionalization and re-hospitalization. As a result of less mobility and activity, delirium and falls become more likely outcomes of functional decline.

Hospital mortality risk categorization in patients with acute decompensated heart failure has been addressed by Fonarow et al. [23]. establishes which hospitalized individuals pose the greatest danger of death. Methods like regression tree analysis and categorization help with this process. One kind of predictive analytics is the use of trees for classification and regression purposes. Each node in the tree stands for a condition, attribute, or feature related to the result. The model can calculate the probability of an event happening by combining these nodes. Afterwards, the model may be used to identify individuals who are more likely to die while hospitalized and to direct their care accordingly.

The Vasoactive-inotropic score (VIS) is a tool for predicting newborn mortality and morbidity during cardiopulmonary bypass (CPB), as mentioned by Gaies et al. [24]. The amounts of vasoactive and inotropic medications given to the baby before, during, and after CPB are used to compute the VIS. The purpose of these medications is to control the patient's pulse and blood pressure. The VIS is thought to be a reliable indicator of post-CPB mortality and morbidity rates as it represents the infant's level of hemodynamic instability. There is an increased risk of death and morbidity associated with hemodynamic instability, as shown by higher VIS scores. Mortality, length of hospital stay, and need for vasopressor and inotropic support are all negatively correlated with higher VIS scores, according to studies. Clinicians may

use the VIS to identify babies who may need vigorous treatment and closer monitoring following CPB, as it is a strong predictor of prognosis in this setting.

Heart failure with preserved ejection fraction (HFpEF) is a new categorization method that Shah et al. [25] have addressed. It relies on phenotypic trait analysis, which includes biomarkers, electrocardiogram results, clinical profile, laboratory data, and demographics. A more thorough and relevant HFpEF categorization system based on the disease's unique characteristics is what Phenomapping aims to give. Better patient care and longer survival times will result from this categorization system's increased precision in diagnosing and grouping patients with HFpEF. Additional study into the route physiology of HFpEF can be conducted on the Phenomapping platform, which will enhance our knowledge of the illness and open the door to new therapies.

Disadvantages

- Data complexity: currently available machine learning algorithms for neonatal cardiac arrest detection need to be able to correctly understand big and complicated datasets.
- Access to data: In order for machine learning models to provide reliable predictions, they often need massive datasets. The reliability of the model could be compromised if there is a lack of data in enough amounts.
- Misabeled data: Current ML models can only learn as much as the data used to train them. The accuracy of the model's

predictions is dependent on the accuracy of the data labels.

4. PROPOSED SYSTEM

With the current setup, ml models can determine which elements are most important for the disease and how likely it is that a newborn will have an arrest. As a result, these statistical models have to be used to enhance the early identification and intervention of cardiac arrest in infants [17].

Predicting and detecting neonatal cardiac arrest using machine learning is becoming more common. When the heart abruptly stops pumping blood, it causes a potentially fatal condition known as cardiac arrest. Death or long-term brain damage may result. Newborn cardiac arrest has been difficult to diagnose early on because of the condition's intricacy. But that is all changing thanks to machine learning [18].

Medical records, vital signs, and other physiological data are examples of the kinds of complicated data that machine learning algorithms go through in vast quantities. The algorithms can identify data patterns that might indicate a cardiac arrest and notify the appropriate authorities. As an example, one research analyzed the vital signs of neonates, including heart rates, breathing patterns, and more, in order to apply machine learning to identify indicators of cardiac arrest. Signs of cardiac arrest might be recognized by the algorithm as much as eight hours before traditional techniques could. Newborns' odds of survival and the severity of the condition's effects might both

be greatly enhanced by this. The likelihood of cardiac arrest in infants is also anticipated with the use of machine learning. Machine learning algorithms can investigate the illness's potential dangers by poring over mountains of patient data. It may aid doctors in determining which infants are most likely to have a cardiac arrest and getting them the treatment they need. Newborn cardiac arrest detection is being transformed by machine learning [19].

Machine learning algorithms can analyze complicated data sets to identify neonates at risk of cardiac arrest and detect symptoms of the disease. This innovation has the potential to lessen the impact of cardiac arrest on infants and save lives. One important thing about machine learning models for newborn cardiac arrest detection is that they may pick up on changes in vital indicators like heart rate, respiration rate, and oxygen saturation that are hard to see with the human eye. Newborns at risk of cardiac arrest may be identified and treated promptly with this early detection method [20]. Better long-term disease management is another benefit of using machine learning models to examine patient data and give individualized guidance and treatment.

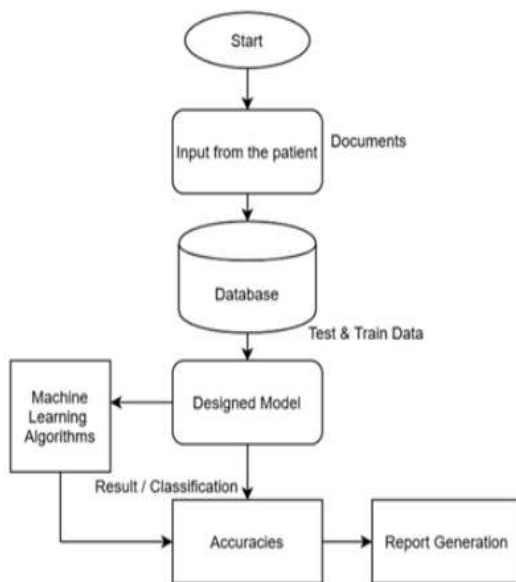
Advantages

Newborns' vital indicators linked to cardiac arrest were automatically and reliably recognized.

- The capacity to detect even minute changes in the baby's vital signs that may point to an impending cardiac arrest.
- The capacity to recognize infants at high risk of cardiac arrest.

- Heart attacks may be detected early on, which means that therapies can be done quickly to enhance the result.
- Less time and money spent on conventional monitoring techniques.
- Better results for patients as a result of quicker response times to cardiac arrest.

5. SYSTEM ARCHITECTURE



6. IMPLEMENTATION

Modules

Service Provider

A valid username and password are required for the Service Provider to access this module. Once he logs in, he'll have access to features like the ability to browse and train and test traffic data sets, You may see the results of the trained and tested accuracy in a bar chart. You can also see the prediction of the kind of cardiac arrest, the ratio of the predicted types of arrests, and the predicted data sets that have been downloaded. See the

Results of the Cardiac Arrest Type Predicted Ratio, See All Users From a Distance.

View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Here, the administrator may see the user's information (name, email, and address) and grant them access.

Remote User

All all, there are n users in this module. Registration is required prior to performing any operations. Details will be entered into the database after a user registers. He will need to log in using the permitted username and password when registration is completed. After logging in, users will be able to do things like see their profile, predict when a cardiac arrest may occur, and register and log in.

7. CONCLUSION

Because it allows for the efficient and reliable identification of newborns at high risk of cardiac arrest, the proposed statistical model based on machine learning is vital for the early diagnosis of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU). When it comes to vital signals like heart rate and breathing rate, machine learning models can detect even the most minute alterations that might signal a cardiac arrest. The suggested CMLA was able to achieve the following values in a training (Tr) comparison region: 0.912 delta-p, 0.894 FDR, 0.076 FOR, 0.859 prevalence threshold, and 0.842 CSI. The suggested CMLA achieved test-specific values of

0.896 for delta-p, 0.878 for FDR, 0.061 for FOR, 0.844 for prevalence threshold, and 0.827 for CSI in a testing (Ts) comparison range. By using the suggested cardiac machine learning model to detect babies who are at danger, medical professionals may intervene early, perhaps preventing a devastating tragedy. Babies spend less time in the CICU when cardiac arrest is detected early, which helps save money and improves outcomes. Improving the suggested model in the future will center on identifying important signs of cardiac arrest utilizing real-time data. It may include taking readings of vital signs including temperature, respiration rate, heart rate, and other physiological metrics. After collecting this data, cardiac machine learning algorithms may examine it to create models that reliably forecast when a cardiac arrest is likely to occur. In order to facilitate earlier and more successful actions, medical personnel may be alerted using the suggested methodology. Using AI to spot trends in the data and improve forecast accuracy is another potential improvement for the future. Additional information, such as medical records and past records, might be included. Lastly, these models have the potential to be used in order to provide individualized interventions for individuals, leading to therapies that are more successful overall. Predicting possible problems in fetuses or newborns might also be possible with an improved version of the suggested machine learning method. Prenatally, a healthcare team may assess a baby's risk for certain cardiac problems and intervene more effectively if necessary. The suggested machine learning approach also has the

potential to enhance medical diagnosis and treatment. Doctors may get better, more current information when they diagnose a patient by looking at their medical records. This improves diagnosis. Better patient outcomes, earlier interventions, and less expensive therapies are all possible outcomes.

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