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# Neonatal Cardiac Monitoring for Early Intervention of New Born Babies

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**ABSTRACT:** Improving the accuracy of diagnostic tool detecting Early cardiac arrest in newborn babies. This includes the utilization of imaging techniques like echocardiography and computed tomography, alongside advancing the creation of a Cardiac Machine Learning model (CMLM) using statistical methods. The CMLM utilizes physiological parameters to predict cardiac arrest events in newborns within the Cardiac Intensive Care Unit (CICU). In training comparisons, the proposed CMLA achieved high performance metrics, including delta-p value of 0.912, False Discovery Rate (FDR) of 0.894, False Omission Rate (FOR) of 0.076, prevalence threshold value of 0.859, and CSI value of 0.842. Similarly, in testing comparisons, the CMLA showed promising results with a delta-p value of 0.896, FDR of 0.878, FOR of 0.061, prevalence threshold value of 0.844, and CSI value of 0.827. Executing The plan this framework in the CICU is expected to significantly reduce mortality and the morbidity linked to cardiac arrest in significant innewborns by enabling early recognition and intervention.

## I. INTRODUCTION

Cardiac arrest occurring in newborn babies is a condition requiring early detection for optimal care and long-term health understanding associated signs and symptoms, and risk factors is vital common signs, unresponsiveness, or decreased movement, Factors increasing the risk comprise low birth weight family history, preterm birth, difficult delivery, or maternal high blood pressure.

Early detection involves regular monitoring of heart and respiratory rates using pulse oximetry or auscultation. Statistical models like Logistic Regression, Naive Bayes, and Support Vector Machines aid in early detection. These models analyse factors such as birth weight, gestational age, and gender to predict the likelihood of cardiac arrest. Machine learning further enhances early detection by analysing complex data like vital signs, allowing for timely intervention. By detecting subtle changes, high-risk babies can be identified, reducing mortality rates and improving outcomes. The proposed research automates critical sign detection, identifies subtle changes indicating cardiac arrest, and recognizes high-risk babies. Early detection enables timely interventions, reducing time and cost associated with traditional methods and improving patient outcomes. The manuscript discusses earlier works, proposes a model, provides analytical discussion, comparative analysis, results, conclusion, and future scope. I've condensed the content while retaining the key points about the importance of early detection models and machine learning. Let me know if there's anything else you need!

## II. RELATED WORK

The excerpt you provided outlines various research works and primary concerns linked to early detection in case of cardiac arrest newborn babies, utilizing machine learning techniques. Here's a summary:

1.Key Issues Identified:

- 1.Complexity of Data: Machine learning models must accurately interpret large and complex datasets to detect cardiac arrest in newborns.
- 2.Data Availability: Adequate data availability is crucial for creating accurate predictive models.

- 3. Incorrect Labelling : Accuracy of machine learning models depends on correctly labelled data.
- 4. Overfitting: Models may become too specific capturing noise within the data and leading to inaccurate predictions.
- 5. Unbalanced Data: Imbalance in data can affect model accuracy.
- 6. Model Selection: Choosing the right model for the information is challenging and impacts prediction accuracy.

2. Novelty of Proposed Research: Establishing a baseline for newborns' normal vital signs. Developing leveraging machine learning to build statistical model analyse vital signs. Utilizing predictive analytics to identify risk factors for cardiac arrest. Developing algorithms for detecting subtle changes in vital signs. Utilizing advanced signal processing techniques. Creating an early warning system for medical personnel.

3. Machine Learning Approach: Machine Learning-driven statistical models are essential for the timely identification. Leveraging various data sources to accurately identify patterns and predict cardiac arrest. Helping healthcare providers take proactive steps and intervene promptly. The proposed research aims addressing the challenges in detecting early cardiac arrest in newborns by leveraging methods employing machine learning data analytics, and advanced signal processing methods to improve outcomes and reduce mortality rates.

### III. PROPOSED MODEL

The construction of a cardiac machine-learning model involves several steps: data collection and pre-processing, model selection (usually a neural network), training, evaluation, and deployment. Patient symptoms are inputted and stored in a database, categorized by severity for treatment decisions. The model utilizes advanced algorithms to detect and analyses heart disease using patient records, ECG readings, and clinical images. Feature extraction and data pre-processing are crucial for preparing the information and improving accuracy. The final model classifies analyse and prioritize these features. Features data and detects abnormalities for medical diagnosis and treatment, transforming it into a valuable tool for healthcare professionals.



#### A. SYMPTOMS DATASET

The dataset comprises 84,972 samples from pcap files of newborns in the Cardiac Intensive Care Unit, containing fetal rate (FHR), oxygen saturation (OS), fetal respiratory rate (FRR), body temperature readings, and other medical data. 65% of the data is allocated for training the models, while 35% is reserved for testing. Cross-validation with 20 folds is applied to the training dataset.

#### B. PREPROCESSING

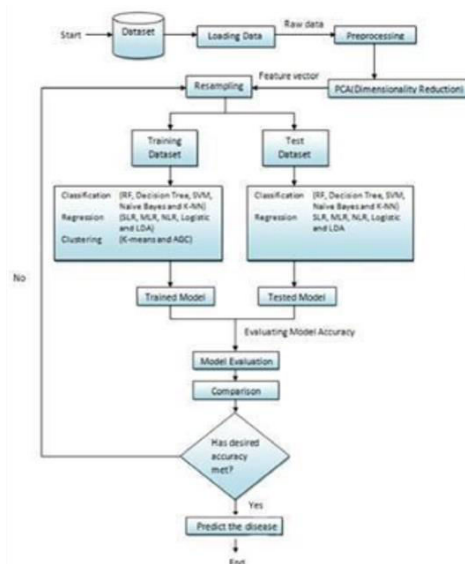
Preprocessing is vital for promptly identifying cardiac arrest in newborns in the Cardiac Intensive Care Unit. It involves cleaning and normalizing data, handling missing values and outliers, and selecting relevant features. This ensures data

suitability in the realm of machine learning algorithms. Key included in the preprocessing involves cleaning the data missing value imputation, data scaling, feature selection, and data transformation to prepare the data for model analysis and comparison

### C.FEATURE EXTRACTION

Feature extraction for early detection of cardiac arrest in newborn babies involves identifying crucial data points from medical records and vital signs. These include Fetal Heart Rate (FHR), fetal movements, maternal vital signs, umbilical cord blood flow, and ultrasound images . Machine learning techniques like selection methods like principle component Analysis (PCA) and recursive feature elimination (RFE) further refine the feature set. Ultimately, these features help build a model for prediction to anticipate cardiac arrest risk, aiding healthcare providers within preventive measures.

D.CLASSIFICATION classification in machine learning is employed for early detect cardiac arrest in newborns by analyzing vital signs data. It involves collecting a dataset, splitting it portioning into training and testing sets training the mode using algorithms like support vector machine or random forest, testing its accuracy, and evaluating its performance to make decisions about a newborn's risk for cardiac arrest basedon unseen data.



### E.PROPOSED ALGORITHM

The cardiac machine learning algorithm uses recurrent neural networks (RNNs) to analyze analyze patient records incorporating vital signs like ECG readings, oxygen saturation, blood pressure, and heart rate to predict impending cardiac arrest in newborns. It extracts features from medical data to create a predictive model, which is evaluated and validation. Finally, it addresses the computational overhead associated with cardiac optimized for accuracy by employing tactics like feature selection parameter tuning. Improvements can be made by including both clinical and imaging data, training on larger datasets, and optimizing for imbalanced data and noise. The algorithm’s performance is assessed by comparing its predations against actual outcomes with the goal of providing early detection and personalized care for newborns at risk of cardiac arrest.

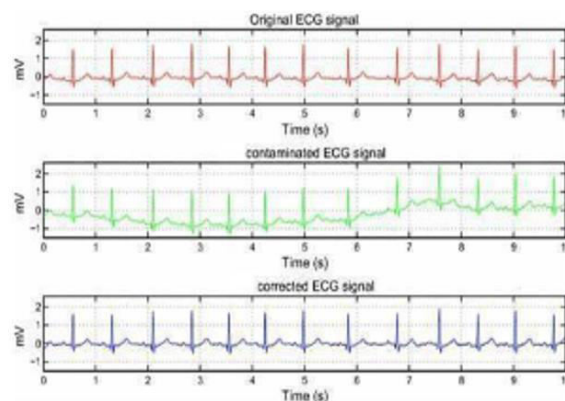
#### Algorithm 1 Cardiac Algorithm for Learning

1. Start;
2. Enter the dataset values;
3. Loading the Raw data inputs;
4. Initiate the pre-processing;
5. Dimensionality reduction using PCA;
6. Obtain the feature vector;
7. Resampling the inputs;

8. Initiate the Training process;
9. Start the Classification, regression and clustering of the Input samples;
10. Obtain the trained model;
11. Initiate the Testing process
12. Start the Classification, regression and clustering of the Input samples;
13. Obtain the tested model;
14. Insert the evaluation parameters as per the training and testing inputs;
15. If (Accuracy = Max.level)
16. Then predict the results for neonates;
17. Else go to step 7;
18. End;

#### IV. ANALYTICAL DISCUSSIONS

Generally, convolutional input data creates temporal patterns in the existing signals. Here the differential signal curves  $T$  and the kernels value of the signal volume can be denoted as  $K$ . convolutional neural network (CNN) architecture for processing input heart signals, particularly focusing on newborns with heart murmur issues. It details the computation of output heart signal values, feature vector extraction, and classification using a sigmoid function. Additionally, it discusses medical treatments, functional treatments, and preventive measures for cardiac diseases. The motivation for developing a cardiac machine learning algorithm is outlined, along with steps to overcome challenges such as limited data availability and model table machine learning models, which depends on factors like dataset size, model complexity, and computational architecture.



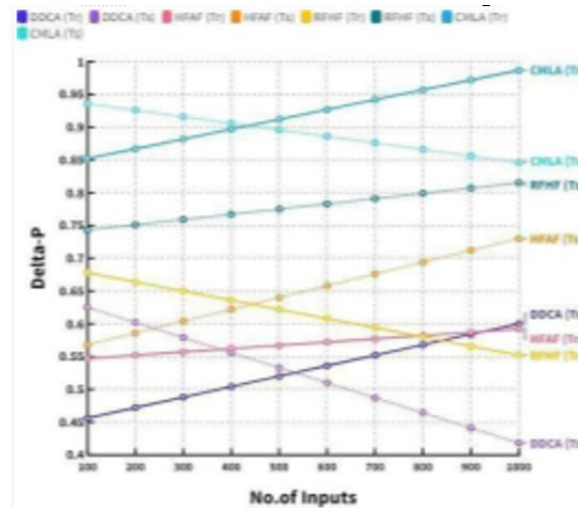
#### V. COMPARATIVE ANALYSIS

The Machine (MLA) was compared with existing methods for cardiac amyloidosis detection (DDCA), Heart Failure and Atrial Fibrillation diagnosis (HFAF), and Heart Failure risk factors assessment (RFHF). MATLAB r2022a was used for simulations. Table 2 summarizes the simulation parameters for the MLA environment.

##### A. COMPUTATION OF DELTA-P

DeltaP (1 p) values are a measure of the difference in pressure between the left and right ventricles of the heart in newborn babies in the Cardiac Intensive Care Unit (CICU). This measure is used to detect early signs of cardiac arrest in newborns. The values are calculated by taking the difference between the peak systolic pressure of the left ventricle and the peak diastolic pressure of the right ventricle. A high deltaP (1 p) value can indicate a possible cardiac arrest, and can alert medical staff to take appropriate action to prevent the condition from becoming more serious.  $1p = PPV + NPV - 1$ ; (9) where, PPV represents the positive predicted value and NPV represents the negative predicted value  $PPV = \frac{P_t}{P_t + P_f}$  where,  $P_t$  represents the true positive prediction,  $P_f$  represents the false positive prediction,  $N_t$  represents the false negative prediction values. Now substitute the eq, 9,3 shows the various variation between proposed and existing models. In that  $T_r$  represents the training data and  $T_s$  represents the testing data different level of inputs. In a training ( $T_r$ ) comparison proposed CMLA reached 0.912 delta-p value. Meanwhile the DDCA reached 0.52, HFAF reached 0.567 and RFHF reached 0.622 delta-p values respectively. In testing ( $T_s$ ) comparison region, the proposed CMLA

reached 0.533, HFAF reached



**B. COMPUTATION OF FALSE DISCOVERY RATE (FDR)**

The False Discovery Rate (FDR) measures the accuracy of results in a clinical trial or study, specially in the context of detecting cardiac arrest in newborn in the Cardiac intensive care unit. It quantifies the proportion of false positive among all positives identified in the study. A lower FDR indicates more accurate results, aiding clinicians in identifying at-risk patients and intervening effectively. FDR is computed using the formula  $FDR = 1 - PPV$ , where PPV is the positive predicted value. Table 4 presents FDR evaluations between proposed and existing models, with Tr representing training data and Ts representing testing data. Additionally, Fig. 8 illustrates FDR evaluation across different input levels, showing the proposed CMLA achieving FDR values of 0.894 in the training (Tr) region and 0.878 in the testing (Ts) region, outperforming DDCA, HFAF, and RFHF models.

**C.COMPUTATION OF FALSE OMISSION RATE (FOR)**

The False Omission Rate (FOR) measures the percentage of undetected cardiac arrests in newborns in the cardiac Intensive Care Unit by the Early Detection System. It's crucial for assessing the systems effectiveness in identifying and responding to cardiac arrests. A lower indicates better performance, while higher values suggest a need for improvement. Fig. 7, demonstrates the Evaluation of Delta-P in improvement. FOR is calculated as  $FOR = 1 - NPV$ , where NPV is the negative predicted value. Table 5 displays FOR testing data. Additionally, Fig. 9 depicts FOR evaluations between proposed and existing true positive evaluation across different input levels, showing the prediction (Pt), False positive prediction (Pf), true negative proposed CMLA achieving FOR values of 0.076 in the prediction (Nt), and false negative prediction (Pf). The training (Tr) region and 0.061 in the testing (Ts) region, evaluation of Pth is compared between different models demonstrating superior performance compared to using training (Tr) and testing (Ts) data. The proposed DDCA, HFAF, and RFHF models.model (CMLA) generally outperforms other models, reaching higher Pth values both in training and testing scenarios. Specifically, in the training region, CMLA reached a Pth value of 0.859, while in the testing region, it reached 0.844. Comparatively, other models like DDCA, HFAF, and RFHF achieved lower Pth values in both regions.

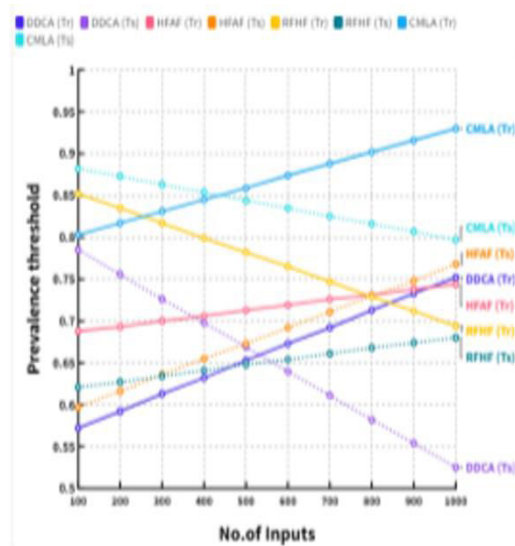
**D. COMPUTATION OF PREVALENCE THRESHOLD (Pth)**

The prevalence threshold (Pth) is the minimum number of cardiac arrests in a population before early detection in newborn babies in the Cardiac Intensive Care Unit (CICU) is considered necessary. It's calculated based on incidence rates and guides when early detection should be implemented. The formula for Pth involves positive false rate (PFR), positive true rate (PTR),true positive false rate (PFR) ,true positive prediction (pt), false positive prediction (pf), true Improvement. FOR is calculated as  $FOR = 1 - NPV$ , where NPV is the negative predicted value. Table 5 display FOR evaluations between proposed and existing true positive prediction (pt), false positive prediction (Pf), true negative in the prediction (Nt), and false negative prediction (Pf). The region, evaluation of Pth is compared between different models to using training (Tr) and testing (Ts) data. The proposed model (CMLA) generally outperforms other models, reaching higher Pth values both in training and testing scenarios. Specifically, in the training region, CMLA reached

0.844. comparatively, other models like DDCA, HFAF, and RFHF achieved lower Pth values in both regions.

**E. COMPUTATION OF CRITICAL SUCCESS INDEX(CSI)**

The Critical Success Index (CSI) measures the effectiveness of early detection and treatment of cardiac arrest in newborns in the Cardiac Intensive Care Unit (CICU). It's calculated by dividing the quantity of successfully detected and treated cardiac arrests through the entire quantity of cardiac arrests within a certain period. The CSI helps healthcare providers assess their early detection efforts. The formula for CSI involves true positive prediction (Pt), false positive prediction (Pf), true negative prediction (Nt), and false negative prediction (Pn). Comparing different models using training (Tr) and testing (Ts) data shows that the proposed CMLA model outperforms others, achieving higher CSI values both in training (0.842) and testing (0.827) scenarios. In contrast, other models like DDCA, HFAF, and RFHF have lower CSI values in both regions.



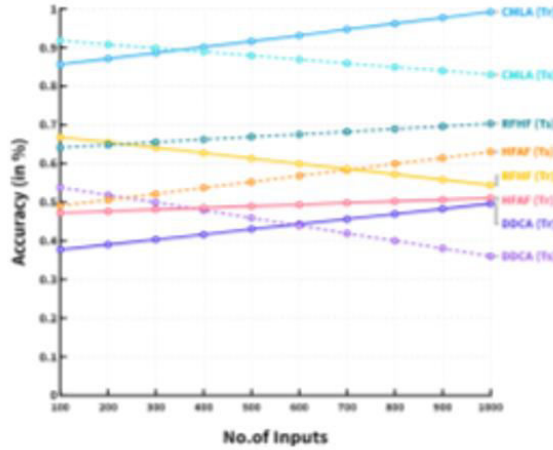
Negative prediction (Nt), and false negative F.

**F.COMPUATION OF ACCURACY (A)**

The accuracy of a Cardiac Machine Learning Model (CMLM) for early detection of cardiac arrest in newborns in the cardiac Intensive Care Unit (CICU) is crucial. Its assessed by comparing predicted outcomes with observed metrics. Sensitivity measures true positives, while specificity measures true negatives. The accuracy is calculated as the mean of sensitivity and specificity. Comparing different models using training (Tr) and testing (Ts) data reveals that the proposed CMLA model in the training and 0.879 in testing. In contrast, other models like DDCA, HFAF, and RFHF have lower accuracy values in both regions

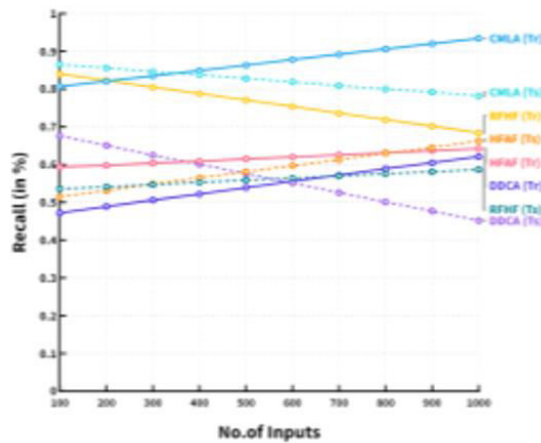
**G.COMPUTATION OF RECALL (R)**

The CMLMs ability identify positive, like cardiac arrest cases in newborns. Its calculated by determining true positive (TP) And False negative (FN) Table 10 compares recall scores of proposed and existing models on training (Tr) and testing (Ts) Data. In the Tr region, the proposed CMLA achieved the highest recall of 0.863, followed by RFHF (0.771), HFAF (0.615), and DDCA (0.539) . In the Ts region, the proposed CMLA had a recall of 0.828, outperforming DDCA (0.576), HFAF (0.581), and RFHF (0.559).



#### H. COMPUTATION OF F1-SCORE (F1)

The F1 score integrates precision and recall to measure a model's accuracy. Precision is true positives divided by total positives, while recall is true positives divided by actual positives. The F1 score ranges from 0 to 1, with higher scores indicating better identification of positives. Table 11 compares F1 scores of proposed and existing models on training (Tr) and testing (Ts) data. In Tr, the proposed CMLA achieved the highest F1 score for 0.846, followed by RFHF (0.760), HFAF (0.529), and DDCA (0.463). In Ts, the proposed CMLA had an F1 score of 0.811, outperforming DDCA (0.494), HFAF (0.499), and RFHF.



### VI. RESULTS AND DISCUSSION

Statistical models in cardiac intensive care units use vital signs data to detect potential cardiac arrest cases in newborns, aiding timely intervention. Table 12 compares the convergence regarding performance metrics among proposed and existing models on training (Tr) and testing (Ts) data. In Tr, the proposed CMLA outperformed others with higher values across metrics like delta-P, false discovery rate, accuracy, precision, recall, and F1-score. Similarly, in Ts, the proposed CMLA showed superior performance. Table 13 summarizes mean values of performance parameters, reaffirming the superiority regarding proposed CMKA model over existing ones. Additionally, the Cardiac Machine Learning Model for Early Prediction of sepsis in the ICU is highlighted for its capacity to accurately identify sepsis at a premature stage, using supervised and unsupervised algorithms machine learning, thus aiding in timely intervention and treatment.

### VII. CONCLUSION

The proposed machine learning-based statistical model is crucial in order to detect early of cardiac arrest in newborns in the Cardiac Intensive Care Unit (CICU), efficiently identifying high-risk infants. In both training (Tr) and testing (Ts)



regions, the proposed CMLA demonstrated superior performance across metrics like delta-P, false discovery rate (FDR), false omission rate (FOR), prevalence threshold, and critical success index (CSI). This timely detection enables interventions, potentially averting tragic outcomes and reducing CICU stays and associated costs. Future enhancements aim to incorporate real-time data, including various physiological measures, to develop models for accurate prediction and alerting medical staff for early interventions. Additionally, leveraging artificial intelligence and historical patient data can further enhance diagnostics, treatments, and personalized interventions, potentially extending to predicting complications in fetuses or newborns, improving prenatal interventions, and providing increased accuracy and cost-effective treatment.

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