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NEONATAL CARDIAC ARREST PREDICTION USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

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 Cardiac 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 echocardiography 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 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.

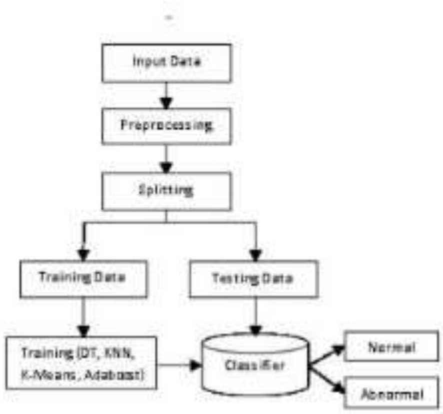
INDEX : newborn babies, medical emergency, cici, cmla

I. INTRODUCTION

Neonatal cardiac arrest prediction using machine learning algorithms is a vital area of research aiming to enhance early detection and intervention in newborns at risk. By analyzing various physiological parameters and medical data, ML models can forecast the likelihood of cardiac arrest, enabling healthcare providers to administer timely interventions and improve outcomes for neonates. 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 [1]. The most common signs and symptoms of cardiac arrest in newborn babies area 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. Neonatal cardiac arrest is a critical medical event with potentially severe consequences for newborns. Predicting cardiac arrest in this population is particularly challenging due to their unique physiological characteristics and the rapid onset of cardiac instability. Machine learning (ML) algorithms offer a promising approach to overcome these challenges by leveraging vast amounts of data to identify subtle patterns and risk factors associated with cardiac arrest in neonatal.

ML models can analyze a diverse range of variables including vital signs, heart rate variability, respiratory parameters, laboratory results, and clinical notes to generate predictive algorithms. These models can then continuously monitor neonatal patients, alerting healthcare providers to early signs of cardiac instability and enabling timely intervention. Furthermore, ML algorithms can be tailored to specific clinical contexts and patient populations, allowing for personalized risk assessment and intervention strategies. Additionally, ongoing refinement and validation of these algorithms with real world data can improve their accuracy and reliability over time. Overall, the integration of ML-based predictive analytics into neonatal intensive care units holds the potential to revolutionize the management of neonatal cardiac arrest, ultimately leading to improved outcomes and reduced mortality rates in this vulnerable population.

V. SYSTEM ARCHITECTURE



VI. METHODOLOGY

Proposed Algorithm

1. Start;
2. Enter the dataset values;
3. Loading the Raw data inputs;
4. Initiate the preprocessing;
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;

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. The various representations of this are given below based on eq. 1,

$$a_i^x[v] = \alpha_i\left(\sum_{i=0}^{T-1} \beta_i^x d_1^i[v-i] + \delta_i^x\right); \tag{1}$$

where, α is expressed an activation function, β indicated a weight of the kernel and δ are indicated as the bias of the input signal. d[v] expressed the input signal value. Here the output signal values are fed into the convolution layer. Then the kernel value is equal to double of the signal value. Now the non-overlapped segments of the input heat signals are expressed in eq. 2,

$$r_i^x[v] = \max\max\left\{a_i^x[u]\right\}_{u=(v-1)U+1}^{v*U}; \tag{2}$$

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Now to compute the output heart signal values as per the newborns present heart rate. If the newborn has the heart murmur issues, then the computation results have some harmonic disturb from the murmur sound. So, we need to confirm the length of the output signal is equal to the non-overlapping of other signals. This has shown in the following eq. 3,

$$s_i^x[v] = r_i^x[v]; \tag{3}$$

where, s^x_i [v] denotes the length of the output signals and the r^x_i [v] expressed the non-overlapped signals. The upper segment signals need to be reduced as per the computed redundant segment results. Now the second segment kernel values has expressed in the eq. 4,

$$d_j^x[v] = \alpha_j\left(\sum_{j=1}^{K}\sum_{i=0}^{T-1}\beta_{i*j}^{x} d_1^j[v-i] + \delta_{i*j}^{x}\right); \tag{4}$$

where, α is expressed an activation function, β indicated a weight of the kernel and δ are indicated as the bias of the input signal. d[v] expressed the input signal value. Now we need to obtain the feature vector values as per the received convolutional signals. The Analyzed various intensive care ECG signals has demonstrated in the fig. 5,

$$b_{G1} = \max\max\left\{a_j^x[u]\right\}; \tag{5}$$

Finally the classification has to expressed as the following eq. 6,

$$C = \frac{1}{1+e^{-(\beta * b_{G1}+\delta)}}; \tag{6}$$

Here the cost function has computed to minimize the entropy values of binary heart rate signals without any harmonic disturbance.

$$F_{cost} = \sum_i a_i\left[h_i^{(original)} \ln\ln(C_j) + \left(1-h_i^{(original)}\right)\ln\ln(1-C_i)\right]; \tag{7}$$

where, the h_i are the natural strength of the predicted signals values at the sample weights. The SVM prediction has computed with the help of below eq. 8,

$$h_i^{(Prediction)} = sign\left(\delta + \sum_{i=1}^{N}\beta_i{}^*K(u,u_i)\right); \tag{8}$$

congestive heart failure. The following medications may also be prescribed:

- Non-steroidal anti-inflammatory - with a pronounced reactiontoinfectionbythe‘‘forces’’ofinnatei mmunity;
- Angioprotectors - if vascular damage is observed;
- Penicillin-based antibiotics - when the deficiency is triggered by pathogenic bacteria;
- Cardiovascular therapy - for the treatment of acute failure.

Functional treatments: Surgical intervention is the only way to completely eliminate defects in the cardiovascular system. Sometimes the only way to save a child is to do it this way. The Surgery is recommended if you have the following symptoms:

- After the slightest physical exertion, the patient immediately develops shortness of breath, and other symptoms of insufficiency are also observed;
- Diagnostics shows the pathological expansion of any cardiac chambers and its task for ‘‘wear and tear’’;
- Pressure increases in one ventricle.

It is impossible to effectively treat the defect without following the correct regimen of the child:

- The patient’s diet should be balanced, rich in calcium, magnesium, potassium and manganese (most of them in oats, barley, buckwheat, apples and prunes). At the same time, it is undesirable to pay attention to salt and pickled foods, preservation. It is better to eat in small portions, but often.
- A child should go to bed on time, as proper rest significantly reduces the burden on the heart.
- The patient should be protected from situations that lead to overwhelm or frustration. It is also not recommended to mount it physically.
- If the weather is comfortable, regular walking is essential.

The motivation for developing a Cardiac machine learning algorithm is to provide a more accurate and reliable method for diagnosing and prognosis cardiac diseases. The challenges of developing such an algorithm include limited availability of data, the need for robust feature selection, and the need to improve the efficiency and accuracy of the algorithms. Additionally, the lack of expert resources for validating and verifying the machine learning models poses a significant challenge. Understanding and manipulating the complex relationships between the clinical features that need to be captured to create a successful model is complex. Finally, the models must be constantly updated to remain relevant and practical. Motivation is essential in any machine learning algorithm, especially for diagnosing, predicting, and tracking cardiac health. It is important to remember that sustaining

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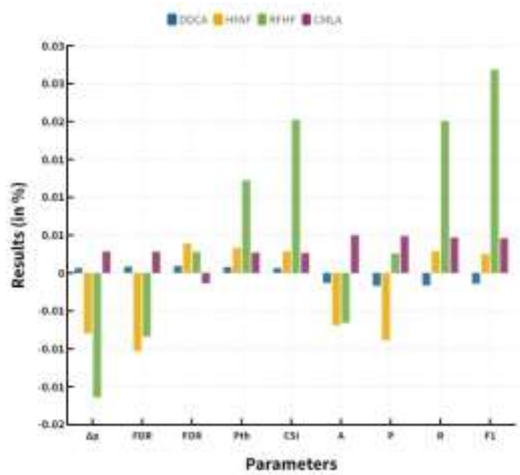
motivation can be complex for any learner and that the challenge posed by algorithms exists within that larger context. To help overcome the motivation and challenges the cardiac machine learning algorithm poses, learners should focus on a few key steps.

- First and foremost, it is essential to understand the data and algorithms that go into developing the machine learning model. It can better understand the problem domain and give the learner meaningful feedback on their progress and performance.
- Second, they should break the problem down into smaller, achievable goals. When doing so, it is essential to focus on the basics, such as understanding the machine learning techniques, implementing different models, and tuning the parameters.
- Third, learners should consider using visualization methods to understand the data better and enhance their problem-solving skills. For example, they create flow charts, timelines, or network diagrams that can help explain complex relationships within the data.
- Finally, learners should use reinforcement learning to improve the machine learning model's performance over time. Reinforcement learning takes a trial-and-error approach to machine learning, continually adjusting and refining its results.

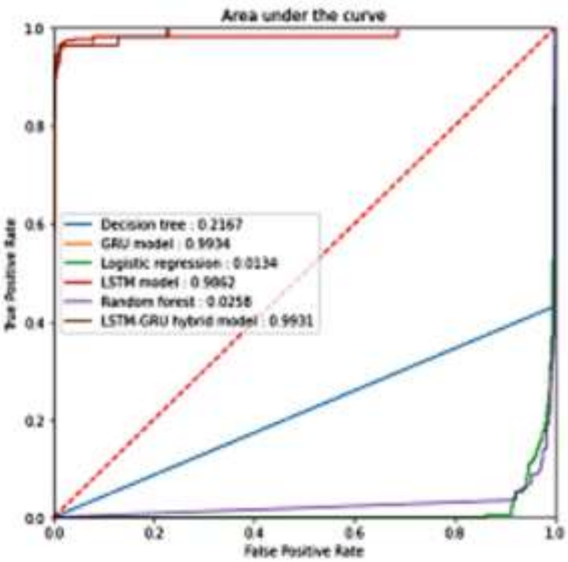
These steps will help learners reach their motivation and challenge goals when working on a cardiac machine learning algorithm.

RESULTS ANALYSIS

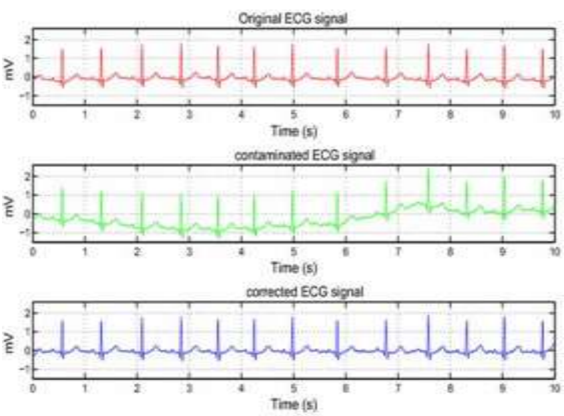
Analyzed various intensive care ECG signals.

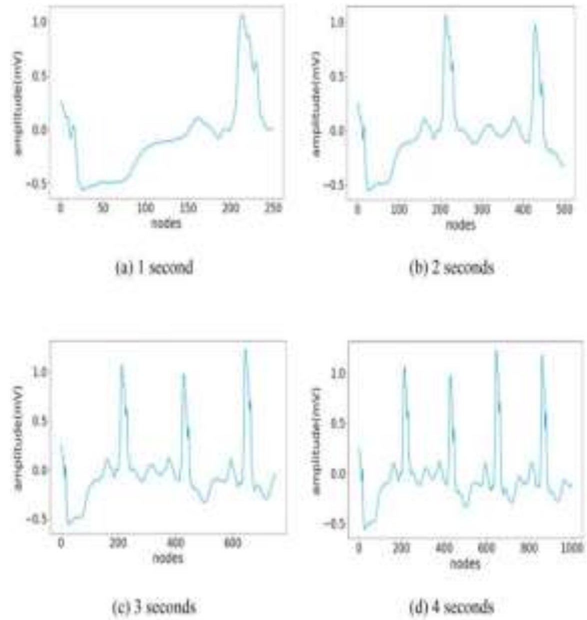


Mean values of the performance parameters

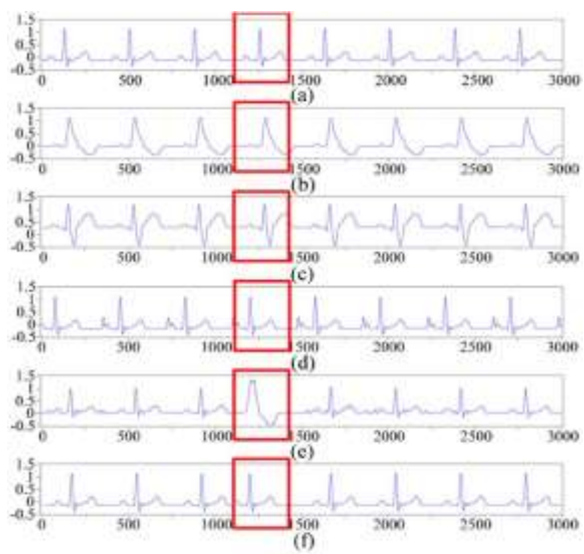


False Positive Rate (FPR) vs. True Positive Rate (TPR)





Preventive measures of the analytical results.



Various heart rates monitoring in continuous evaluation.

CONCLUSION

Heart is one of the essential and vital organ of human body and prediction about heart diseases is also important concern for the human beings so that the accuracy for algorithm is one of parameter for analysis of performance of algorithms. Accuracy of the algorithms in machine learning depends upon the dataset that used for training and testing purpose. When we perform the analysis of algorithms on the basis of dataset whose attributes are shown in TABLE.1 and on the basis of confusion matrix, we find KNN is best one.

FUTURE ENHANCEMENT

For the Future Scope more machine learning approach will be used for best analysis of the heart diseases and for earlier prediction of diseases so that the rate of the death cases can be minimized by the awareness about the diseases.

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