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RESEARCH ARTICLE

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 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 TERMS Cardiac arrest, newborn, early detection, intensive care unit, statistical modeling.

I. INTRODUCTION

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 are a 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. Risk factors that may increase the likelihood of cardiac arrest in newborn babies include low birth weight, a family history of cardiac arrest, preterm birth,

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a difficult delivery, or a mother with a history of high blood pressure during pregnancy [2]. A baby's medical history should also be evaluated for any potential risks. In order to ensure early detection of cardiac arrest in newborn babies, regular monitoring of the baby's heart rate and respiratory rate is essential. It can be done through pulse oximetry, a non-invasive, painless procedure that measures the amount of oxygen in the baby's blood [3]. Additionally, auscultation, or listening to the baby's heart rate and breathing with a stethoscope, can also help to detect any irregularities in the baby's heart rate or breathing. Early detection of cardiac arrest in newborn babies is vital to provide the best care for these infants and ensure their long-term health. By understanding the signs and symptoms of this condition and being aware of the risk factors that may put a baby at an increased risk of cardiac arrest, parents and medical professionals can work together to ensure the best possible outcomes for these babies [4]. The early detection of cardiac arrest in newborn babies can be achieved using Statistical Models. Statistical models are mathematical techniques used to analyze and draw conclusions from data. These models are powerful tools in the medical field, as they can help predict, diagnose, and treat certain diseases and conditions [5]. One example of a statistical model used for the early detection of cardiac arrest in newborn babies is the Logistic Regression model. This model uses data collected from the baby's medical history, such as birth weight, gestational age, and gender, to create a predictive model to determine the likelihood of cardiac arrest [6]. This model can help doctors identify those babies at risk and can help them decide whether to treat the baby with medication or perform surgery to correct the issue. Another model used for the early detection of cardiac arrest in newborn babies is the Naive Bayes model [7]. This model uses a probabilistic approach to analyze data and identify patterns to make predictions. The model can identify high-risk babies and help doctors determine the best course of action to take [8]. The Support Vector Machine model is another statistical model used for the early detection of cardiac arrest in newborn babies. This model uses data collected from the baby's medical history and other sources to create a predictive model that can determine the likelihood of cardiac arrest [9]. This model can identify those babies at risk and help doctors decide on the best course of treatment. Statistical models are powerful tools that can be used for the early detection of cardiac arrest in newborn babies [10]. These models can help doctors identify those at risk so that they can provide the best possible treatment for the baby. Furthermore, these models can help doctors determine the best course of action to take in order to prevent or reduce the likelihood of cardiac arrest [11].

Cardiac arrest in newborns is a life-threatening medical condition that requires immediate medical attention. Early detection and intervention can improve the outcomes of these infants and reduce mortality rates. Statistical models are powerful tools that can be used to identify risk factors and predict the likelihood of cardiac arrest [12]. Logistic regression is one of the best statistical models for the early detection of cardiac arrest in newborns. This model allows researchers to quantify the relationship between risk factors and the probability of experiencing an arrest [13]. It can be used to identify the most critical factors associated with cardiac arrests, such as gender, gestational age, and birth weight [14]. Logistic regression can also be used to calculate the odds ratio for each risk factor, which indicates how much more likely an infant is to experience an arrest if they have a particular risk factor. Another effective model for the early detection of cardiac arrest in newborns is a support vector machine (SVM) [15]. This model type is well-suited for binary classification tasks, such as classifying an infant as either healthy or having experienced a cardiac arrest. It can also be used to identify important risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest [16]. Finally, artificial neural networks (ANNs) can also detect cardiac arrest in newborns. ANNs are powerful machine-learning models that can learn complex patterns from data. These models can be used to identify risk factors associated with cardiac arrest and predict the likelihood of an infant experiencing an arrest. Logistic regression, support vector machines, and artificial neural networks are all effective models for the early detection of cardiac arrest in newborns. These models can be used to identify the most critical risk factors associated with the condition and predict the likelihood of an infant experiencing an arrest. Therefore, these statistical models should be used to improve newborns' early detection and intervention of cardiac arrest [17]. Machine learning is increasingly used to predict and detect cardiac arrest in newborn babies. Cardiac arrest is a life-threatening condition in which the heart suddenly stops beating, and blood flow to the brain and other organs stops. It can lead to permanent brain damage or death. Due to the complexity of the condition, early detection of cardiac arrest in newborns has been difficult. However, machine learning is changing that [18]. Machine learning algorithms analyze large amounts of complex data, such as patient medical histories, vital signs, and other physiological data. The algorithms can detect patterns in the data indicative of cardiac arrest and alert medical personnel. For example, one study used machine learning to detect signs of cardiac arrest in newborns by analyzing their heart rates, breathing patterns, and other vital signs. The algorithm detected signs of cardiac arrest up to eight hours before conventional methods. It could significantly improve the chances of survival for newborns and reduce the damage caused by the condition. In addition, machine learning is used to predict newborns' risk of cardiac arrest. By analyzing large amounts of patient data, machine learning algorithms can identify risk factors associated with the condition. It can help medical personnel identify newborns at an increased risk of cardiac arrest to receive the care they need. The machine learning is revolutionizing the early detection of cardiac arrest in newborns [19]. By analyzing large amounts of complex data, machine learning algorithms can detect signs of cardiac

arrest and identify newborns at an increased risk of the condition. This technology could save lives and reduce the damage caused by cardiac arrest in newborns. The critical contribution of machine learning models used for the Early Detection of Cardiac Arrest in Newborn Babies is that these models can detect subtle changes in vital signs such as heart rate, respiratory rate, and oxygen saturation that are difficult to detect with the naked eye. This early detection can help to identify newborns at risk of cardiac arrest and allow for timely intervention and treatment [20]. Additionally, machine learning models can be used to analyze patient data to provide personalized advice and care to patients, enabling better long-term management of their condition. The following are the critical contribution of the proposed research works.

- Automated and accurately detected critical signs associated with cardiac arrest in newborn babies.
- Ability to recognize subtle changes in the baby's vital signs that can indicate potential cardiac arrest.
- Ability to identify high-risk babies likely to suffer from cardiac arrest.
- Early detection of cardiac arrest, enabling timely interventions that can improve the outcome.
- Reduction in the time and cost associated with traditional monitoring methods.
- Improved patient outcomes due to early diagnosis and treatment of cardiac arrest.

The remaining chapters of the manuscript have organized as the following. Chapter 2 provides information about the earlier works related to the research. Chapter 3 provides the construction of the proposed model. It includes the proposed algorithm and flow chart. Chapter 4 details the analytical discussion, and Chapter 5 shows the comparative analysis between the proposed and existing models. Chapter 6 expresses the results and discussion, and finally, chapter 7 expresses the conclusion and future scope of the proposed research.

II. RELATED WORKS

Carlisle et al. [21] has discussed the Heart failure is when the heart cannot pump enough blood to the rest of the body. Various conditions, including high blood pressure, coronary artery disease, and diabetes, can cause it. Atrial fibrillation is an arrhythmia (irregular heartbeat) in which the heart's upper chambers (atria) beat rapidly and irregularly. It can cause a decrease in the amount of blood pumped to the rest of the body, leading to symptoms such as shortness of breath and fatigue. Atrial fibrillation is a common cause of heart failure. Heart failure and atrial fibrillation treatment usually involve medications to control the heart rate and rhythm, lifestyle changes, and sometimes surgery to repair or replace the heart. Yaku et al. [22] has discussed the Risk factors for functional decline during hospitalization in very old patients with acute decompensated heart failure include age, gender, co-morbidities, and frailty. In addition, complex medical problems, the need for aggressive treatments, and the presence of cognitive impairment may increase the risk of functional decline. Clinical outcomes associated with a functional decline during hospitalization in very old patients with acute decompensated heart failure include increased length of stay, healthcare utilization, mortality, and decreased quality of life. The functional decline may also lead to higher rates of re-hospitalization, as well as an increased risk of institutionalization. Additionally, the functional decline may lead to an increased risk of falls and delirium due to decreased mobility and activity levels. Fonarow et al. [23] has discussed the Risk stratification for in-hospital mortality in acutely decompensated heart failure determines which patients are at higher risk of dying while in the hospital. It is done by using classification and regression tree analysis. Classification and regression tree analysis is a type of predictive analytics that uses trees to classify and predict outcomes. The trees are nodes representing various conditions, characteristics, or features associated with the outcome. Using a combination of these nodes, the model can determine the likelihood of a particular outcome occurring. The model can then be used to identify patients at a higher risk of in-hospital mortality and to guide the treatment of the patient.

Gaies et al. [24] has discussed the Vasoactive–inotropic score (VIS) is designed to predict morbidity and mortality in infants after cardiopulmonary bypass (CPB). The VIS is calculated from the levels of vasoactive and inotropic drugs administered to the infant during and after CPB. These drugs are used to regulate the patient's blood pressure and heart rate. The VIS is believed to accurately predict post-CPB morbidity and mortality because it reflects the degree of hemodynamic instability in the infant. Higher VIS scores indicate greater hemodynamic instability and, therefore, a greater risk of morbidity and mortality. Studies have found that higher VIS scores are associated with increased mortality, extended hospital stays, and an increased need for vasopressor and inotropic support. The VIS is a significant predictor of outcome after CPB and can help clinicians identify infants who may require closer monitoring and more aggressive management. Shah et al. [25] has discussed the Phenomapping is a novel classification system for heart failure with preserved ejection fraction (HFpEF). It is based on the analysis of phenotypic characteristics, such as demographics, clinical profile, laboratory values, electrocardiographic findings, echocardiography findings, and biomarkers. The goal of Phenomapping is to provide a more comprehensive and meaningful classification system for HFpEF that is based on the distinct phenotypes of the disease. This classification system will enable clinicians to more accurately diagnose and stratify patients with HFpEF, leading to better management and improved outcomes. The Phenomapping system also provides a platform for further research into the underlying path physiology of HFpEF, allowing for a better understanding of the disease and the potential for improved treatments. Lee et al. [26] has discussed the Heart failure with preserved or reduced ejection fraction (HFPEF or HFREF) is a form of heart failure in which the heart's ability to pump blood

is impaired, but the amount of blood pumped from the heart with each beat (ejection fraction) is either normal or reduced. The underlying cause of this type of heart failure is poorly understood, but various disease pathologies and risk factors have been associated with it. Disease pathologies, such as coronary artery disease, hypertension, and diabetes, can lead to HFPEF or HFREF. These conditions can impede blood flow through the heart and its associated vessels, accumulating fluid in the lungs and other parts of the body. Additionally, these diseases can cause damage to the heart muscle and its inner lining, making it more difficult for the heart to pump blood efficiently. Risk factors for HFPEF or HFREF include advancing age, obesity, gender, smoking, and alcohol consumption. People who are older, overweight, and lead an unhealthy lifestyle are more likely to develop HFPEF or HFREF. Additionally, gender may play a role, as women are more likely to develop HFPEF than men.

Saeed et al. [27] has discussed the Multiparameter Intelligent Monitoring in Intensive Care (MIMIC) is a system that uses artificial intelligence and machine learning algorithms to continually monitor a patient's health and vital signs in an intensive care unit (ICU) setting. MIMIC is designed to alert healthcare providers to changes in a patient's condition that may require medical intervention. It is an effective tool for detecting subtle changes in a patient's condition that clinicians may find difficult to detect with only physical exams and laboratory tests. The system can monitor vital signs, including heart rate, respiration rate, blood pressure, and temperature. Additionally, MIMIC can detect changes in a patient's oxygen saturation and provide alerts when abnormalities are detected. By combining data from multiple sources and using advanced analytics, MIMIC can provide early warnings and enable healthcare providers to make more informed decisions about a patient's care. Lee et al. [28] has discussed the Predicting mortality among patients hospitalized for heart failure is an essential task for healthcare professionals. It is essential to identify those at higher risk of death so that they can receive more aggressive treatment and better management of their condition. The study aimed to develop a clinical model to predict mortality among patients hospitalized for heart failure accurately. To do that, researchers used data from an extensive database of patient records to identify risk factors associated with mortality. They used various statistical methods to evaluate the risk factors and develop a predictive model. Gianfrancesco et al. [29] has discussed the Potential biases in machine learning algorithms using electronic health record (EHR) data can come from various sources. First, there may be biases in the data due to sampling or coding errors. If the data used to train the algorithm does not represent the population, the algorithm may be biased toward specific outcomes. Second, there may be biases in how the algorithm processes the data, such as favoring certain data types or giving too much weight to certain variables. Third, there may be biases in evaluating the algorithm, such as using metrics that favor specific outcomes or data sets that do not reflect the full range of potential outcomes. Finally, there may be biases in how the algorithm is deployed, such as using the algorithm to make decisions that favor specific outcomes.

Moor et al. [30] has discussed the Sepsis is a life-threatening condition caused by an overwhelming immune response to an infection, and it is one of the leading causes of death in intensive care units (ICUs). Early detection and intervention are essential for successful treatment, and machine learning algorithms can help to identify sepsis patients in the ICU at an earlier stage. To identify sepsis-associated patterns, machine learning algorithms can analyze various data sources, such as patient vital signs, laboratory test results, and medical history. These algorithms can be trained to identify sepsis patients earlier, allowing clinicians to intervene before the patient's condition deteriorates. Using machine learning algorithms in the ICU to predict and diagnose sepsis earlier can reduce mortality, morbidity, and length of stay. Furthermore, this technology can help to reduce costs associated with sepsis-related complications and improve the quality of care provided to patients. Deo et al. [31] has discussed the predictive model was then validated by comparing its predictions to actual mortality rates among a separate group of patients. The model accurately predicted mortality among patients with heart failure, indicating its effectiveness in identifying those at high risk of death. This study highlights the importance of using predictive models to identify those at high risk of death among patients hospitalized for heart failure. Such models can help healthcare professionals manage and treat patient's better, improving outcomes and patient safety.

Shankar et al. [33] have discussed deep synergic learning as a powerful AI technique that allows machines to interpret data and create strategies for intelligent decision-making. When applied to healthcare diagnosis for COVID-19, this technology has the potential to identify the disease accurately and quickly. This approach can diagnose individuals and populations in connected living and imaginative city scenarios. The system applies layers to detect patterns, identify trends, extract relevant information, and eventually find the best possible diagnosis and management solutions. The machine can learn more accurately and quickly by combining medical evidence with other data sources, such as symptoms, environment, location, and lifestyle factors. Synergic deep learning can help to reduce diagnostic time, improve accuracy and reliability, eliminate errors and delays, and identify insights about the disease. It also helps healthcare providers make better-informed choices in prescribing treatments and further develop strategies and guidelines to prevent future outbreaks. Hashash et al. [34] has discussed MEC-Based Energy-Aware Distributed Feature Extraction for mHealth Applications with Strict Latency Requirements, a technique in which feature extraction for mHealth applications is distributed across multiple edge nodes using Mobile Edge Computing (MEC) technology. MEC-based feature extraction distributes a load of feature extraction among the edge nodes to reduce the

energy consumed, making the whole system energy-aware. Feature extraction is made more efficient through data preprocessing, data augmentation, ensemble training, and data cleansing techniques. Furthermore, the distributed feature extraction techniques ensure that the latency requirements are met, as the feature extraction process is distributed among more nodes, resulting in shorter latency for each node. Chaudhary et al. [35] has provided a motor imagery classification using sparse nonnegative matrix factorization (SNMF) and convolutional neural networks (CNNs) is a technique used to classify motor imagery data acquired from electroencephalography (EEG). The SNMF decomposes the EEG signals into latent features that are then used as input to a CNN for classification. The objective of this technique is to effectively capture the spatial and temporal patterns of motor imagery data while maintaining interpretability. The technique is supervised in that the labels of the signal segments are known in advance. The SNMF is used to reduce the dimensionality of the data, making it more suitable for classification, while the CNNs are used to learn an interpretable classification space. By combining the two, a more efficient and effective motor imagery classification can be achieved. Bhatti et al. [36] has discussed a Soft computing-based EEG classification by optimal feature selection and neural networks, a technology that uses neural networks and evolutionary algorithms to classify brain activity in electroencephalogram (EEG). The approach is based on optimizing feature selection and neural network structure to find the most accurate model. It uses a combination of traditional machine learning algorithms and optimization techniques for feature selection, such as Genetic Algorithms and Particle Swarm Optimization. Once the optimal feature set and structure have been determined, a feed-forward neural network is trained to recognize the patterns in the EEG signal and classify them. The network is trained using back-propagation, a standard gradient descent algorithm that measures the output error and adjusts the weights accordingly. The result is an accurate, reliable EEG classifier that can be used to detect and classify various types of brain activities.

Luo et al. [37] has discussed a machine learning-based risk stratification tool for in-hospital mortality of intensive care unit patients with heart failure is a tool that uses machine learning (ML) to identify patterns in patient data that can be used to determine their risk of mortality while they are in the ICU. The tool aggregates patient data such as age, medical history, ICU severity scores, laboratory values, and other data to generate a risk stratification score. The higher the score, the greater the chance of mortality. The tool can help healthcare providers predict and treat heart failure cases by identifying high-risk patients. It, in turn, allows for earlier interventions and improved outcomes for these patients. Winslow et al. [38] has discussed that a machine learning early warning score can significantly impact hospital mortality. This kind of system would use data analysis to evaluate the health of a hospitalized patient and generate a score that reflects the patient's risk of death. Healthcare providers can then use this score to predict a patient's future health outcome, identify high-risk patients, and take appropriate action to reduce the mortality rate. By tracking vital signs and other physiological parameters and patient behavior, this type of system can provide valuable insight into patient health and allow for early interventions to prevent more severe complications. By increasing the accuracy and scope of patient risk assessment, a machine learning early warning score can ultimately save more lives. Ahsan et al. [39] has discussed a Machine Learning-based heart disease diagnosis as a promising technique for identifying patients with a high risk of developing cardiovascular diseases or conditions. It uses the data collected from the patient's medical history and other relevant sources to recommend treatments or preventive treatments. The machine learning models are trained to recognize patterns and trends in the patient's data, such as the patient's body weight and blood pressure readings. The models can identify patterns that indicate a high risk of developing heart disease and develop an alert system to alert the doctor. By providing early detection and timely treatments, machine learning-based heart disease diagnosis can help prevent the development of more severe complications. Rooney et al. [40] has discussed that Machine learning and high-frequency physiologic data can be used to predict extubation failure in pediatric cardiac ICUs. This technique uses physiological variables captured at up to 10 Hz to create a snapshot of a patient's health status. Then, machine learning algorithms are used to analyze the data, detect changes in the patient's condition, and determine the risk of extubation failure. It can help doctors identify those patients at risk for extubation failure and take measures to prevent it. This technique can also be used to compare outcomes across different ICUs and can help inform clinical decisions.

Kropat et al. [41] has discussed a computational networks and systems. It refers to the use of networks and devices to solve a variety of problems using an established technique called homogenization. Homogenization is the process of turning different problems into one or more homogeneous problems that can be solved more easily. This technique was developed to reduce complexity and to enable precise solutions of variation problems on architectures with large models such as micro-architecture networks and devices. This technique simplifies and speeds up the solving process by considering the same problem from different perspectives and reducing it into a single problem. This allows the use of computer resources in a more efficient manner and also helps in keeping the problem size relatively smaller so that it does not create system problems. Özmen et al [42] has discussed a robust optimization in spline regression models is a technique used to optimize multi-model regulatory networks under polyhedral uncertainty. This technique utilizes spline regression models to identify regulatory networks even when uncertainty exists in the data. The models used are robust in that they are tolerant of data outliers

and perturbations, which are often present in complex regulatory networks. Additionally, the models are capable of achieving robust and efficient results by considering the polyhedral uncertainty of the data points, which can vary greatly depending on the number of variables in each model. As a result, robust optimization in spline regression models is a powerful tool for accurately predicting the behavior of multi-model regulatory networks. Onak et al. [43] has discussed the Evaluation of multivariate adaptive non-parametric reduced-order model for solving the inverse electrocardiography problem is a method for predicting cardiac activities from electrocardiographic signals. It uses a combination of adaptive non-parametric regression and reduced order modeling to estimate the parameters of the cardiac activity sources from observed ECG signals. The adaptive non-parametric regression model is used to learn a priori knowledge of the cardiac source activity parameters from the observed ECG. The reduced order modeling methodology is then used to reduce the high dimensionality of the adaptive non-parametric regression model and to improve the accuracy of the solution. Evaluation of the multivariate adaptive non-parametric reduced-order model for solving the inverse electrocardiography problem indicates that it can be used to accurately reconstruct cardiac source activities from electrocardiographic signals. This is a promising novel approach to solving the difficult problem of unsupervised inverse electrocardiography. Alparslan-Gök et al. [44] has discussed the cooperation under interval uncertainty is the process of two or more agents working together to solve a problem or achieve a goal despite the fact that their exact values or knowledge may be uncertain. This is usually done in a way that all parties benefit from the outcome, or at least not worse off than when they started. Examples include cooperative game theory, multi-agent negotiation, and distributed problem solving.

Hegazy et al. [45] has discussed a cancer treatment-related cardiac dysfunction and heart failure in children is diagnosed through a combination of medical history, physical examination, imaging studies, and laboratory tests. These include an echocardiogram to measure heart function, an electrocardiogram to measure the electrical activity of the heart, and cardiac biomarker tests to detect abnormal heart muscle damage. Clinicians may also request additional tests, such as cardiac catheterization or magnetic resonance imaging, to evaluate the structure and function of the heart. Vasichkina et al. [46] has discussed a cardiac involvement may manifest in the form of myocarditis, or inflammation of the myocardium, which affects the heart's ability to function properly. Myocarditis is one of the most common causes of heart failure, arrhythmias, or heart rhythm problems, and sudden cardiac death. It can also lead to cardiac arrest, a sudden loss of heart function. Other signs and symptoms of cardiac involvement in COVID-19-affected children may include chest pain, palpitations, and changes in heart rate. Some COVID-19-tiny patients may also have signs of pericardial effusion, or fluid accumulation in the area around the heart. On physical examination, signs of fluid accumulation may include an enlarged or tender precordial region and a pericardial friction rub. Altemose et al. [47] has discussed a neonatal hypertension can have many causes including disorders of the cardiovascular system, endocrine system, or kidneys. It can also result from certain medications, severe infections, a large sized for gestational age baby, or if the baby is small for gestational age. When left untreated, neonatal hypertension can lead to serious complications, such as seizures, poor feeding, and developmental delays. In some cases, it can even lead to organ damage or premature death. Due to the seriousness of this condition, it is important for all neonatal intensive care unit physicians to remain vigilant in its diagnosis and treatment. Bleiweis et al. [48] has discussed a Ventricular Assist Device is a type of mechanical device used to support the circulation of blood through the circulatory system of a neonate or infant with a failing functionally univentricular circulation. It works by helping the heart pump blood to the body and absorbing some of the work it has to do. This device usually consists of an electric motor that is attached to a pump which communicates with the heart and produces a flow of blood all throughout the body. This device can help reduce the workload on the heart which may lead to improved overall circulation and heart function.

From the above literature works, the following key issues were identified. They are

- The complexity of data: Most of the existing machine learning models must be able to accurately interpret large and complex datasets to detect cardiac arrest in newborn babies.
- Data availability: Most machine learning models require large amounts of data to create accurate predictions. If data is unavailable in sufficient quantities, then model accuracy may suffer.
- Incorrect labeling: The existing machine learning models are only as accurate as the data trained using the input dataset. If the data has been incorrectly labeled, the model cannot make accurate predictions.
- Over fitting: It is a common problem in machine learning models where the model needs to be more specific and capture more noise from the data, resulting in inaccurate predictions.
- Unbalanced data: Unbalanced data can also lead to inaccurate predictions as the model may not be able to detect unusual patterns.
- Model selection: Choosing a suitable model for the data is a challenging task. There are a variety of models to choose from, and selecting the wrong model could lead to accurate predictions and better results.

Early detection of cardiac arrest in newborn babies is essential to ensure their survival and health. If cardiac arrest is not identified and treated quickly, it can cause permanent damage to the baby's heart and other organs, leading to long-term health problems. Early detection of cardiac arrest allows for immediate treatment, improving the chances of survival and long-term health for the newborn. Early detection also

allows the baby to receive necessary medical care to prevent further complications or death. The novelty of proposed research work has the following.

- Establish a baseline for newborn babies' normal range of vital signs. This baseline can monitor any changes in the vital signs that could indicate a potential cardiac arrest.
- Developing a statistical model using machine learning techniques to analyze the vital signs of newborn babies. This model can identify patterns and trends in the vital signs indicative of an impending cardiac arrest.
- Utilizing predictive analytics to identify risk factors associated with cardiac arrest in newborn babies. It can help in predicting the likelihood of cardiac arrest before it occurs.
- Develop an algorithm that can detect the subtle changes in the vital signs indicative of an impending cardiac arrest. This algorithm can alert medical personnel when a potential cardiac arrest is detected.
- Utilizing advanced signal processing techniques to identify the subtle changes in the vital signs that may indicate an impending cardiac arrest.
- Developing an early warning system that can alert medical personnel during an impending cardiac arrest. This system can help in providing timely medical intervention and reduce mortality rates.

A machine-learning approach using statistical models is an essential tool for the early detection of cardiac arrest in newborn babies. By leveraging data collected from various sources, such as medical records, vital signs, and test results, machine learning models can accurately identify patterns and predict the occurrence of cardiac arrest. It can help healthcare providers take proactive steps to prevent the condition or intervene to improve the baby's chances of survival. Machine learning can also help identify risk factors that could lead to cardiac arrest in newborns, allowing medical professionals to take steps to mitigate them. In addition, machine learning models can monitor for signs of cardiac arrest in real time, allowing for prompt and appropriate interventions.

III. PROPOSED MODEL

Constructing the proposed cardiac machine-learning model requires several steps. First, the data must be collected and pre-processed. It includes gathering relevant cardiac data such as electrocardiograms (ECG), other medical images, and any relevant patient information, such as age and gender. The data must then be cleaned and transformed into a format suitable for machine learning algorithms, such as numerical or categorical values. Once the data is ready, a machine-learning model must be selected. It is typically a neural network model, as it can handle the complex relationships between the various data points. The model must then be trained using the data and evaluated for accuracy. If necessary, the model can be tweaked to improve its performance. Finally, the model must be deployed. It involves creating an application or web interface for the model to be used by medical professionals.

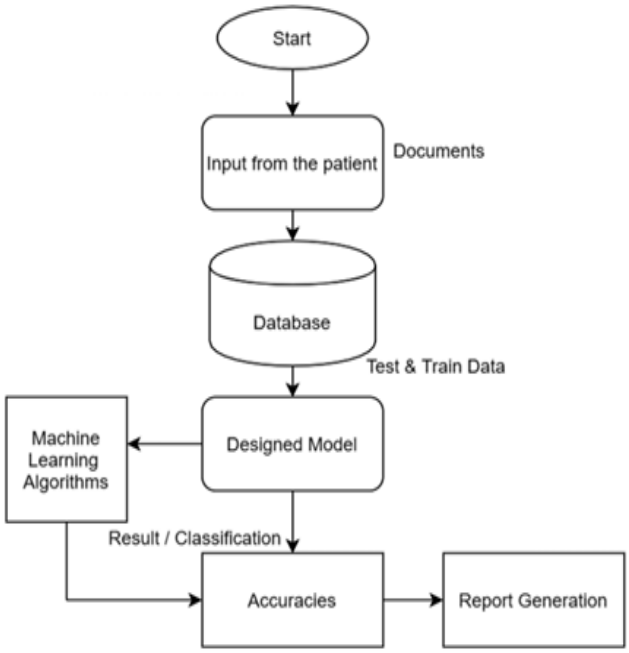

FIGURE 1. Proposed block diagram.

The model should also be continuously monitored for accuracy and necessary adjustments. The block diagram of the proposed machine learning model has shown in the following fig. 1,

In the proposed method, the first detected patient symptoms are given as input. All these data are stored in the database, and their volumes are categorized. These classifications provide information regarding the treatment provided in the standard unit and the treatment provided in the emergency unit, depending on the severity of the illness. The proposed algorithm tests these provided information blocks to predict the severity of the patient's heart block problem. Accurate results are obtained, and treatments are provided for him. It is documented and stored back in the database.

Cardiac Machine Learning model (CMLM) enables the detection and analysis of heart disease via a combination of several advanced machine-learning algorithms. At its core, CML involves creating a model which takes in large amounts of data, such as patient records, electrocardiogram (ECG) readings, clinical images of the heart, and other criteria and processes it to detect and predict cardiac abnormalities. The core components of a typical CML model consist of feature extraction, data pre-processing and model building. The Feature Extraction step converts raw data into meaningful information or features, which a machine learning model can use for further analysis. Feature extraction uses pre-trained algorithms to categorize data points and extract traits that may be essential features in a learning model. The critical features depend on the problem domain; for example, the data may contain patient records, ECGs, and clinical images of the heart for heart disease detection. The model can be better fitted to perform accurate data analysis by extracting

TABLE 1. Symbolic representation detail.

Abbreviation	Meaning
CMLM	Cardiac machine learning model
CICU	Cardiac intensive care unit
Tr	Training data
Ts	Testing data
FDR	False discovery rate
FOR	False omission rate
CSI	Critical success index
SVM	Support vector machine
ANN	Artificial neural network
VIS	Vasoactive–inotropic score
CPB	cardiopulmonary bypass
HFpEF	heart failure with preserved ejection fraction
MIMIC	Multiparameter Intelligent Monitoring in Intensive Care
ICU	intensive care unit
EHR	electronic health record
MEC	Mobile Edge Computing
SNMF	sparse nonnegative matrix factorization
CNN	convolutional neural network
EEG	electroencephalography
ML	machine learning
FHR	contains fetal heart rate
OS	oxygen saturation
FRR	fetal respiratory rate
PCA	Principal Component Analysis
RFE	Recursive Feature Elimination

essential features from these data points. Data pre-processing is a critical part of any machine learning model. It is responsible for cleaning and preparing data for further processing by removing or replacing any noise or outliers. It helps the model focus on the essential features and improves accuracy and efficiency. In the case of CML models, it is essential to prepare the data for input by removing or replacing any missing values and normalizing the data in order to detect any abnormalities in the data accurately. Once the data has been prepared, a model can be built using cardiac machine learning algorithm. With this algorithm, the model can classify the data and detect abnormalities, providing an accurate analysis of the data points, which can then be used for further medical diagnosis or treatment. The core components of a CML model allow for the detection of cardiac abnormalities efficiently and accurately. Combining feature extraction, data pre-processing, and model building, CML models can detect and predict heart conditions quickly and accurately, making them a valuable tool for medical professionals. Table 1, shows the symbolic representation details.

A. SYMPTOMS DATASET

Data construction and modeling are as follows:

- A total of 84972 samples were selected from the data pcap files for the Newborn Babies in the Cardiac Intensive Care Unit [32]. These samples contains fetal heart rate (FHR), oxygen saturation (OS), fetal respiratory rate (FRR), body temperature readings, and other medical constraints
- Totally 65% of data used for training (TR) the models and 35% of data used for testing (TS) the model
- It also used cross-validation on the training dataset with 20-folds.

B. PREPROCESSING

Preprocessing is an essential step in the machine learning approach for Early Detection of Cardiac Arrest in Newborn Babies in the Cardiac Intensive Care Unit. During this stage, the data are prepared for machine learning analysis. This includes cleaning and normalizing the data, selecting the appropriate features, and applying various transformations to the data. Additionally, any missing values or outliers must be identified and addressed. This process ensures that the data is suitable for machine learning algorithms. The data must be split into training, validation, and test sets so that the models can be evaluated and compared. The preprocessing functions would likely include:

- Data cleaning: Remove any duplicate or irrelevant data, fill in missing values, and standardize data formats.
- Missing value imputation: Replace any missing values with meaningful estimates such as the mean of the feature or a prediction from another model.
- Data scaling: Scale the data so that all features have a similar range of values. This can be done using a variety of techniques such as min-max scaling or standardization.
- Feature selection: Select only the most relevant features that will help the model make accurate predictions. This can be done using techniques such as Recursive Feature Elimination or Principal Component Analysis.
- Data transformation: Transform the data into a format that the machine learning model can interpret. This can include one-hot encoding categorical features or applying a logarithmic transformation to skewed features.

Preprocessing functions are necessary in order to clean and prepare the data for a machine learning model. Preprocessing functions can include data cleaning, missing value imputation, data scaling, feature selection, data transformation, and more.

C. FEATURE EXTRACTION

Feature extraction for Early Detection of Cardiac Arrest in Newborn Babies is the process of identifying the most important features from the data that can be used to predict cardiac arrest in newborn babies. This is done by analyzing the patient's medical history, vital signs, and other relevant data. These features can be extracted from the data using various methods such as statistical analysis, machine learning algorithms, and feature selection techniques. Feature extraction

for a machine learning approach for early detection of cardiac arrest in newborn babies can involve the following:

- Fetal Heart Rate (FHR): The FHR can be used to measure the health of the baby. Abnormal FHR patterns can be an indication of cardiac arrest.
- Fetal Movements: A decrease or lack of fetal movements can be a sign of cardiac arrest and can be monitored for early detection.
- Maternal Vital Signs: Maternal vital signs such as blood pressure, heart rate, oxygen saturation, and temperature can be used to indicate the health of the baby. Abnormalities in these vital signs can be an indication of cardiac arrest.
- Umbilical Cord Blood Flow: The umbilical cord blood flow rate can be used to measure the baby's oxygenation levels. Any abnormalities in the blood flow rate can be a sign of cardiac arrest.
- Ultrasound: Ultrasound images can be used to detect any abnormalities in the baby's heart and can be used for early detection of cardiac arrest.

These features can be used by the proposed machine learning algorithms to detect signs of cardiac arrest in newborn babies. For example, a machine learning approach for this task may involve using supervised learning techniques such as decision trees and logistic regression to identify the most important features from the data. This will help to identify the features that are predictive of the risk of cardiac arrest in newborn babies. Furthermore, feature selection techniques such as Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) can be used to further refine the feature set and reduce the number of features required for the predictive model. Once the important features have been identified, they can be used to build a predictive model which can be used to help predict the risk of cardiac arrest in newborn babies. This model can then be used by healthcare providers to take preventative measures to reduce the risk of cardiac arrest in newborn babies

D. CLASSIFICATION

Classification is a supervised learning technique used in machine learning for early detection of cardiac arrest in newborn babies. This technique is used to assign a label to a given input data based on its characteristics. In this case, the input data consists of the baby's vital signs such as heart rate, respiratory rate, body temperature, oxygen saturation, and other medical parameters. The classification algorithm will then analyze these parameters and output a label that indicates whether the baby is at risk of developing cardiac arrest or not. The output label can be either positive or negative, depending on the probability of the occurrence of the condition. The classification operation of a machine learning approach for Early Detection of Cardiac Arrest in Newborn Babies involves several steps. First, a dataset is collected containing information about newborns and their vital signs. This dataset is then split into two sets: a training set and a testing set.

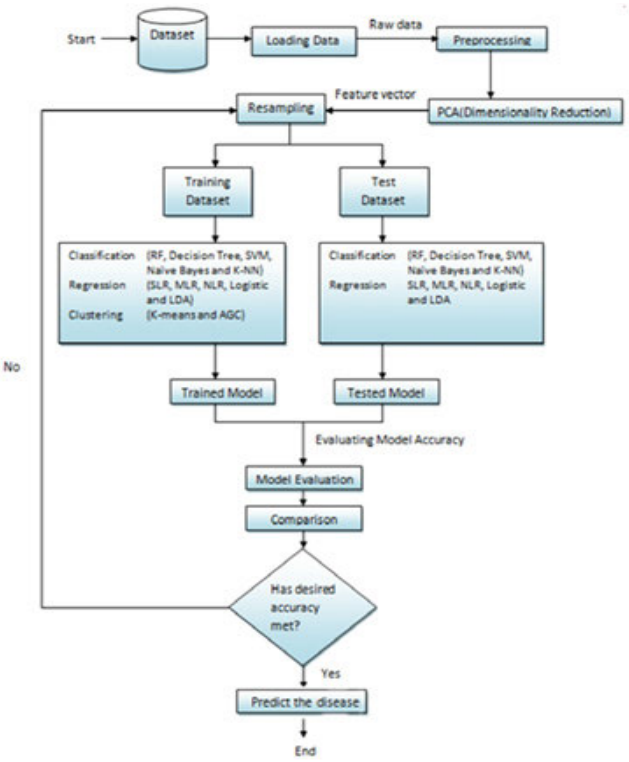

FIGURE 2. Proposed flow diagram.

The training set is used to train a machine learning model using supervised learning algorithms such as support vector machine and random forest. The model is then tested on the testing set to determine its accuracy. The model is evaluated on unseen data to assess its performance. This performance is then used as the basis for making decisions about whether or not a newborn is at risk for cardiac arrest. It can be used to identify patterns in the data and accurately classify them into the correct category.

E. PROPOSED ALGORITHM

Cardiac machine learning algorithms are a type of artificial intelligence (AI) that can be used to detect early signs of cardiac arrest in newborn babies. Fig. 2, illustrates the flow information of proposed model. These algorithms use a combination of data from electrocardiograms (ECGs), stress tests, and other sources to detect abnormalities and predict the likelihood of an adverse cardiac event. By analyzing historical data and identifying patterns, the algorithm can provide early warning signs, before an arrest occurs. This early detection can help doctors to intervene in a timely manner and provide appropriate treatment for the baby. The algorithm can also provide a better understanding of the baby's condition and help doctors to assess their prognosis. This can help to ensure that the baby receives the best possible care and treatment. The algorithm 1, has shown the structure of cardiac machine learning algorithm.

The cardiac machine learning algorithm would use recurrent neural networks (RNN) to analyze patient records.

Algorithm 1 Cardiac Machine Learning 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;

It would be trained on historical data of cardiac arrest in newborn babies and develop an algorithm that could accurately prediction an impending cardiac arrest. It would analyze vital sign records such as electrocardiogram (ECG), oxygen saturation, blood pressure, and heart rate and incorporate any changes in these metrics. It would then be able to alert doctors and nurses of any potential cardiac arrest signals before the patient's heart rate and other vital signs have become too dangerous to treat. Additionally, it would incorporate external triggers, such as risk factors for newborns with cardiac arrest, to further refine its predictions. Finally, it would be able to provide personalized care to newborns at risk for cardiac arrest by predicting and responding quickly to any changes.

The Cardiac machine learning algorithm first extracts features from the patient's medical data such as vital signs, ECG readings, and other clinical information. This data is then used to create a model which can accurately detect early signs of cardiac arrest in newborn babies. The extracted data is then used to create a predictive model which is capable of detecting early signs of cardiac arrest in newborns. This model is based on various machine learning algorithms, such as logistic regression, neural networks, and support vector machines. The performance of the model is then evaluated on a test dataset. This dataset contains the medical data of both healthy and sick newborn babies. The accuracy of the model is then determined by comparing the predictions made by the model against the actual outcomes of the test dataset. Once the model has been evaluated, it can then be optimized to further improve its accuracy. This can be done using various techniques such as feature selection, parameter tuning, and ensembling. The performance of cardiac machine learning algorithms can be improved for early detection of cardiac arrest in newborn babies in a number of ways. First, the data used for training the algorithms should include both clinical data and imaging data. This will help the algorithms to better identify patterns in the data and make more accurate predictions. Second, the algorithms should be trained using a larger dataset. This will help them learn better and detect more subtle patterns in the data. Finally, the algorithms should be optimized to better handle imbalanced data, as well as a variety of noise and artifacts present in cardiac data. By taking these steps, the performance of cardiac machine learning algorithms can be improved for early detection of cardiac arrest in newborn babies. A precompiled method runs based on the given inputs. Its model is explained in Algorithm-1 below. First, the dataset inputs are given. Then their data blocks are loaded, and raw data blocks are available as input. These raw data blocks are now preprocessed, and the resulting results are dimensionally reduced. Thus the raw data block is now inputted with feature vector processing formalized sample blocks. The heart beat segment of neonates has computed with the help of the following fig. 3,

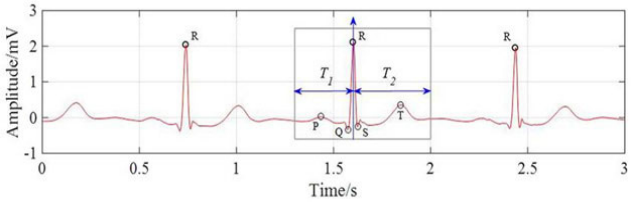

FIGURE 3. Heart beat segment of neonates.

The heart beat segments of neonates are currently, divided into two modules, namely training and testing. The training model is configured with the training dataset module's classification, regression and clustering operations. Currently, test data model results are based on the results obtained through classification and regression in the testing dataset module. Now the results obtained through training and testing are compared. If the two results are compared, and more accurate results are obtained, the prognostic methods of the disease are predicted. The data is then re-sampled when perhaps in results. Currently, the proposed method is working in this class.

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. 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,

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

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,

$$s_i^x[v] = r_i^x[v]; \quad (3)$$

where, s_i^x [v] denotes the length of the output signals and the r_i^x[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,

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

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. 4,

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

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

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

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

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

where, the $h_i^{(original)}$ 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,

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

The various heart rates monitoring in continuous evaluation has demonstrated in the fig. 5,

Medical Treatments: The deficiency cannot be cured by drugs. They are mainly used to relieve the symptoms of

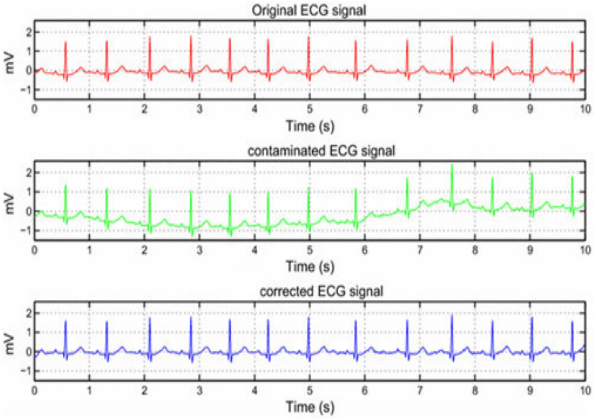

FIGURE 4. Analyzed various intensive care ECG signals.

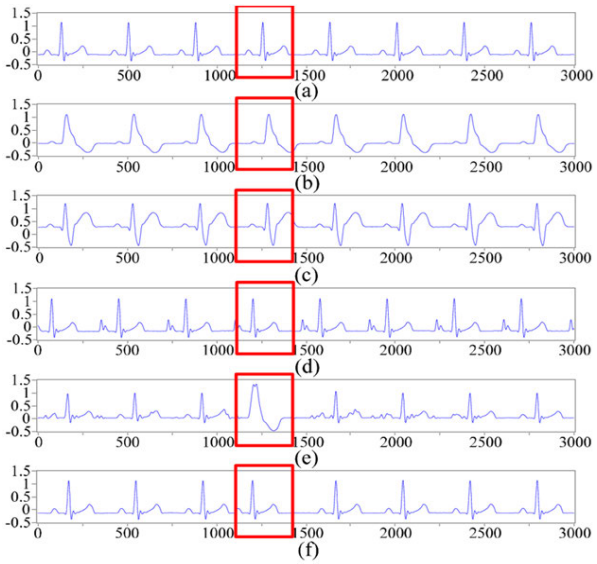

FIGURE 5. Various heart rates monitoring in continuous evaluation.

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

- Non-steroidal anti-inflammatory - with a pronounced reaction to infection by the "forces" of innate immunity;
- 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.

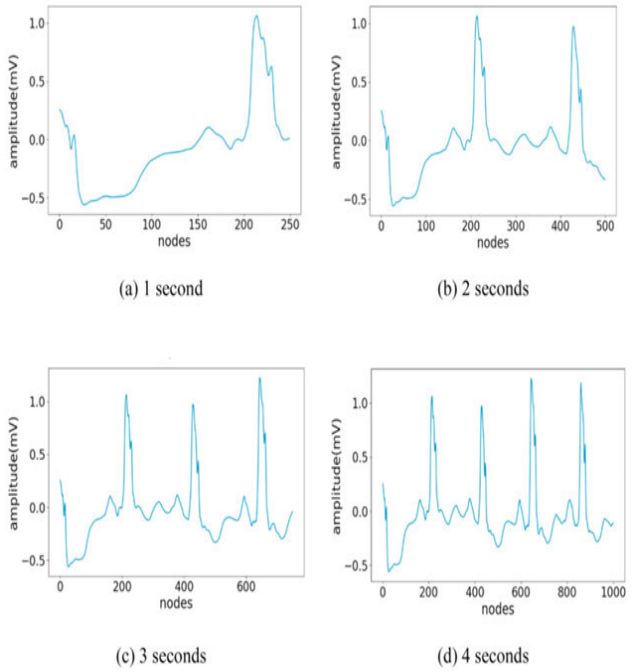

FIGURE 6. Preventive measures of the analytical results.

Preventive measures: The Preventive measures of the analytical results have shown in the fig. 6. 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 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.

The computational overhead of a cardiac machine-learning model depends on the size of the dataset, the complexity of the model being used, and the number of layers the model needs for accurate predictions. In addition, any changes needed to be made to the computational architecture of the model would also need to be considered. As more complex machine learning models are created, the computational overhead costs and complexity typically increase to account for additional layers and complexity. Computational overhead in the cost and complexity of the cardiac machine learning model refers to the resources required to implement, maintain and operate the machine learning models. These resources include hardware (e.g., computing clusters, GPUs, or ASICs), software, and storage. Virtual machines, cloud computing, and clustering components can simplify the cost and complexity of the machine learning model. The computational overhead is an essential aspect of cost and complexity and must be considered when designing a cardiac machine-learning model. It affects the model's scalability, accuracy, and response time and can be optimized via parallelization, which entails running multiple models in parallel. Additionally, computational overhead may include data ingestion, pre-and post-processing of the data, feature engineering, and model training.

V. COMPARATIVE ANALYSIS

The proposed Machine Learning Approach (MLA) has compared with the existing Detection and Diagnosis of Cardiac

TABLE 2. Simulation parameters.

Parameter	Value
Simulation duration	1500 fps
Preamble duration	15ms
Signal detection connectivity	0.2
Frame duration	150ms
Busy state parameter of training session	6
Idle state parameter of training session	5
Busy state parameter of testing session	6
Idle state parameter of testing session	5
Maximum Interference Ratio	0.7
Permission availability	0.5

Amyloidosis (DDCA), Heart Failure and Atrial Fibrillation (HFAF) and Risk Factors for Heart Failure (RFHF). Here the MATLAB r2022a is the tool used for simulation process. The table 2, expresses the simulation parameters of the proposed environment.

A. COMPUTATION OF DELTA-P (Δp)

DeltaP (Δp) 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 (Δp) value can indicate a possible cardiac arrest, and can alert medical staff to take appropriate action to prevent the condition from becoming more serious.

$$\Delta p = PPV + NPV - 1; \tag{9}$$

where, PPV represents the positive predicted value and NPV represents the negative predicted value.

$$PPV = \frac{P_t}{P_t + P_f}; \quad NPV = \frac{N_t}{N_t + N_f}; \tag{10}$$

where, P_t represents the true positive prediction, P_f represents the false positive prediction, N_t represents the true negative prediction and P_f represents the false negative prediction values. Now substitute the eq. 10 in eq. 9,

$$\Delta p = \left\{\frac{P_t}{P_t + P_f}\right\} + \left\{\frac{N_t}{N_t + N_f}\right\} - 1; \tag{11}$$

Table 3, shows the various delta-P evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 7, demonstrates the Evaluation of Delta-P in different level of inputs. In a training (Tr) comparison region, the 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 a testing (Ts) comparison region, the proposed CMLA reached 0.896 delta-p value. Meanwhile the DDCA reached 0.533, HFAF reached 0.64 and RFHF reached 0.775 delta-p values.

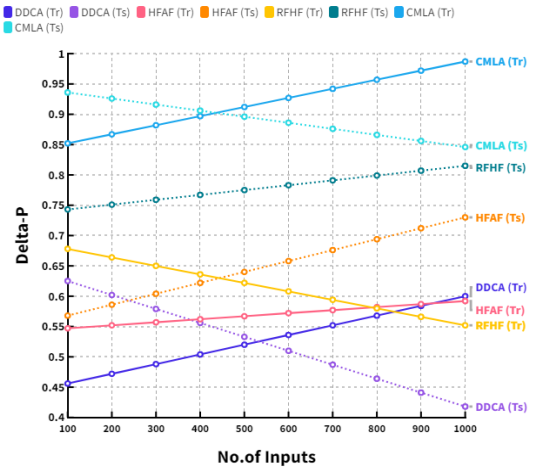

FIGURE 7. Evaluation of Delta-P.

B. COMPUTATION OF FALSE DISCOVERY RATE (FDR)

The False Discovery Rate (FDR) is a statistical measure used to determine the accuracy of results in a clinical trial or study. It refers to the proportion of false positives among all positives identified in the trial or study. In the context of Early Detection of Cardiac Arrest in Newborn Babies in the Cardiac Intensive Care Unit, the FDR is a measure of the accuracy of the study's results in detecting cardiac arrest. The lower the FDR, the more accurate the study's results will be. This is important because it helps clinicians to identify patients at risk of cardiac arrest and intervene to save lives.

$$FDR = 1 - PPV; \tag{12}$$

where, PPV represents the positive predicted value, P_t represents the true positive prediction, P_f represents the false positive prediction. The PPV has obtained in the eq.10.

$$FDR = 1 - \left\{\frac{P_t}{P_t + P_f}\right\}; \tag{13}$$

Table 4, shows the various false discovery rate (FDR) evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 8, demonstrates the evaluation of false discovery rate in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.894 FDR value. Meanwhile the DDCA reached 0.673, HFAF reached 0.734 and RFHF reached 0.805 FDR values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.878 FDR value. Meanwhile the DDCA reached 0.690, HFAF reached 0.828 and RFHF reached 0.875 FDR values.

C. COMPUTATION OF FALSE OMISSION RATE (FOR)

False omission rate values refer to the percentage of cardiac arrests in newborn babies in the Cardiac Intensive Care Unit that are not detected by the Early Detection System. This rate is an important measure of the effectiveness of the system in identifying and responding to cardiac arrests in newborns. A false omission rate of zero may indicate that the system

TABLE 3. Evaluation of Delta-P.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.456	0.625	0.547	0.568	0.678	0.743	0.852	0.936
200	0.472	0.602	0.552	0.586	0.664	0.751	0.867	0.926
300	0.488	0.579	0.557	0.604	0.65	0.759	0.882	0.916
400	0.504	0.556	0.562	0.622	0.636	0.767	0.897	0.906
500	0.52	0.533	0.567	0.64	0.622	0.775	0.912	0.896
600	0.536	0.51	0.572	0.658	0.608	0.783	0.927	0.886
700	0.552	0.487	0.577	0.676	0.594	0.791	0.942	0.876
800	0.568	0.464	0.582	0.694	0.58	0.799	0.957	0.866
900	0.584	0.441	0.587	0.712	0.566	0.807	0.972	0.856
1000	0.6	0.418	0.592	0.73	0.552	0.815	0.987	0.846

TABLE 4. Evaluation of false discovery rate.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.590	0.809	0.708	0.735	0.877	0.839	0.835	0.918
200	0.611	0.779	0.714	0.758	0.859	0.848	0.850	0.908
300	0.632	0.749	0.721	0.782	0.841	0.857	0.865	0.898
400	0.652	0.720	0.727	0.805	0.823	0.866	0.879	0.888
500	0.673	0.690	0.734	0.828	0.805	0.875	0.894	0.878
600	0.694	0.660	0.740	0.852	0.787	0.884	0.909	0.869
700	0.714	0.630	0.747	0.875	0.769	0.893	0.924	0.859
800	0.735	0.600	0.753	0.898	0.751	0.902	0.938	0.849
900	0.756	0.571	0.760	0.921	0.732	0.911	0.953	0.839
1000	0.776	0.541	0.766	0.945	0.714	0.920	0.968	0.829

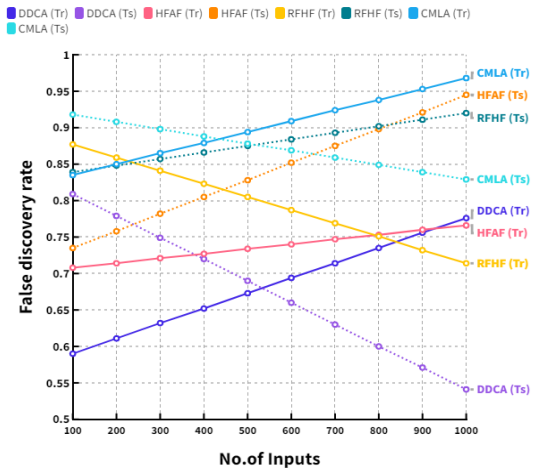

FIGURE 8. Evaluation of false discovery rate.

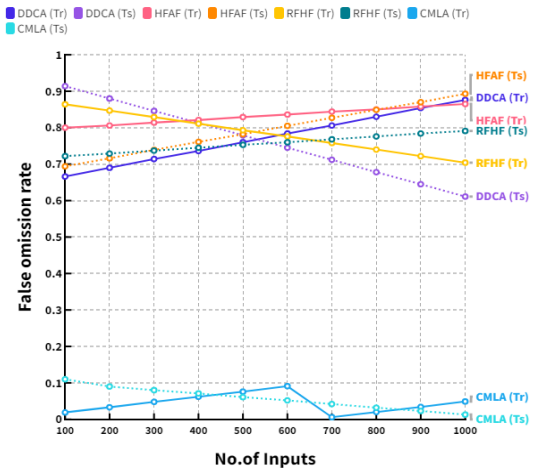

FIGURE 9. Evaluation of false omission rate.

is very effective in detecting cardiac arrests, while high false omission rate values may indicate a need for improvement.

$$FOR = 1 - NPV; \tag{14}$$

where, NPV represents the negative predicted value, Nt represents the true negative prediction, Nf represents the false negative prediction. The NPV has obtained in the eq. 10,

$$FOR = 1 - \frac{N_t}{N_t + N_f}; \tag{15}$$

Table 5, shows the various false omission rate (FOR) evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 9, demonstrates the evaluation of false omission rate (FOR) in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.076 FOR value. Meanwhile the DDCA reached 0.760, HFAF reached 0.829 and RFHF reached 0.793 FOR values respectively. In a testing (Ts) comparison region, the proposed CMLA

TABLE 5. Evaluation of false omission rate.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.666	0.914	0.800	0.694	0.864	0.722	0.019	0.110
200	0.690	0.880	0.806	0.716	0.847	0.729	0.033	0.090
300	0.714	0.846	0.814	0.739	0.829	0.737	0.048	0.080
400	0.736	0.813	0.821	0.761	0.811	0.745	0.062	0.071
500	0.760	0.779	0.829	0.782	0.793	0.753	0.076	0.061
600	0.784	0.745	0.836	0.805	0.776	0.760	0.091	0.052
700	0.806	0.712	0.844	0.827	0.758	0.768	0.006	0.042
800	0.830	0.678	0.850	0.849	0.740	0.776	0.020	0.032
900	0.854	0.645	0.858	0.870	0.722	0.784	0.034	0.023
1000	0.876	0.611	0.865	0.893	0.704	0.791	0.049	0.013

reached 0.061 FOR value. Meanwhile the DDCA reached 0.779, HFAF reached 0.782 and RFHF reached 0.753 FOR values.

D. COMPUTATION OF PREVALENCE THRESHOLD (P_{th})

The prevalence threshold is the minimum number of cardiac arrests that must occur in a given population before Early Detection of Cardiac Arrest in Newborn Babies in the Cardiac Intensive Care Unit (CICU) is considered necessary. The threshold is based on the incidence of cardiac arrest in the population, and serves as a guide to determine when early detection of cardiac arrest should be considered. In general, a prevalence threshold of 2 or more cardiac arrests in a given population is considered to be sufficient to suggest early detection of cardiac arrest as a viable strategy.

$$P_{th} = \left\{ \frac{\sqrt{P_{FR}}}{\sqrt{P_{TR}} + \sqrt{P_{FR}}} \right\}; \tag{16}$$

where, PFR represents the positive false rate, PTR represents the positive true rate, Pt represents the true positive prediction, Pf represents the false positive prediction, Nt represents the true negative prediction and Pf represents the false negative prediction values.

$$P_{TR} = \left(\frac{P_t}{P_t + N_f} \right); \quad P_{FR} = \left(\frac{P_f}{P_f + N_t} \right); \tag{17}$$

Substitute eq. 17 in eq. 16,

$$P_{th} = \left\{ \frac{\sqrt{\left(\frac{P_f}{P_f + N_t} \right)}}{\sqrt{\left(\frac{P_t}{P_t + N_f} \right)} + \sqrt{\left(\frac{P_f}{P_f + N_t} \right)}} \right\}; \tag{18}$$

Table 6, shows the various prevalence threshold evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 10, demonstrates the evaluation of prevalence threshold in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.859 prevalence threshold value. Meanwhile the DDCA reached 0.653, HFAF reached 0.713 and RFHF reached 0.782 prevalence threshold values respectively. In a testing (Ts) comparison region,

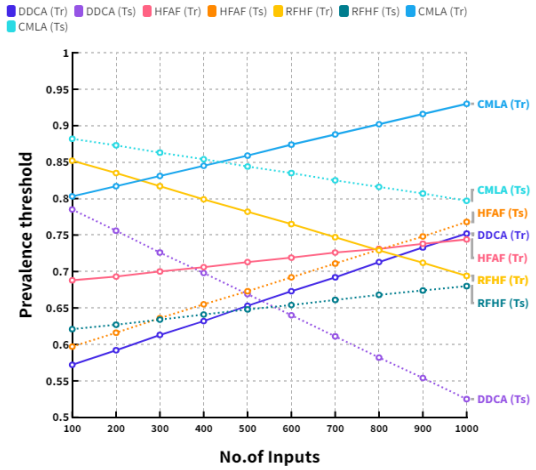

FIGURE 10. Evaluation of prevalence threshold.

the proposed CMLA reached 0.844 prevalence threshold value. Meanwhile the DDCA reached 0.669, HFAF reached 0.673 and RFHF reached 0.648 prevalence threshold values.

E. COMPUTATION OF CRITICAL SUCCESS INDEX (CSI)

The critical success index (CSI) is a metric used to measure the effectiveness of early detection of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU). The CSI is calculated by dividing the number of cardiac arrests that have been detected early and treated successfully by the total number of cardiac arrests that occurred during a certain period of time. This index helps health care providers to understand how successful their early detection efforts are and where to focus their resources for improvement.

$$CSI = \left\{ \frac{P_t}{P_t + N_f + P_f} \right\}; \tag{19}$$

where, PFR represents the positive false rate, PTR represents the positive true rate, Pt represents the true positive prediction, Pf represents the false positive prediction, Nt represents the true negative prediction and Pf represents the false negative prediction values.

Table 7, shows the various critical success index (CSI) evaluations between the proposed and existing models. In that

TABLE 6. Evaluation of prevalence threshold.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.572	0.785	0.688	0.597	0.852	0.621	0.803	0.882
200	0.592	0.756	0.693	0.616	0.835	0.627	0.817	0.873
300	0.613	0.726	0.700	0.636	0.817	0.634	0.831	0.863
400	0.632	0.698	0.706	0.655	0.799	0.641	0.845	0.854
500	0.653	0.669	0.713	0.673	0.782	0.648	0.859	0.844
600	0.673	0.640	0.719	0.692	0.765	0.654	0.874	0.835
700	0.692	0.611	0.726	0.711	0.747	0.661	0.888	0.825
800	0.713	0.582	0.731	0.730	0.729	0.668	0.902	0.816
900	0.733	0.554	0.738	0.748	0.712	0.674	0.916	0.807
1000	0.752	0.525	0.744	0.768	0.694	0.680	0.930	0.797

TABLE 7. Evaluation of critical success index.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.491	0.674	0.592	0.514	0.840	0.534	0.787	0.865
200	0.508	0.649	0.596	0.530	0.823	0.539	0.801	0.856
300	0.526	0.623	0.602	0.547	0.805	0.545	0.815	0.846
400	0.543	0.599	0.607	0.563	0.788	0.551	0.828	0.837
500	0.561	0.574	0.613	0.579	0.771	0.557	0.842	0.827
600	0.578	0.550	0.618	0.595	0.754	0.563	0.857	0.819
700	0.594	0.525	0.625	0.612	0.736	0.569	0.871	0.809
800	0.612	0.500	0.629	0.628	0.719	0.575	0.884	0.800
900	0.629	0.476	0.635	0.643	0.702	0.580	0.898	0.791
1000	0.646	0.451	0.640	0.661	0.684	0.585	0.912	0.781

Tr represents the training data and Ts represents the testing data.

Fig 11, demonstrates the Evaluation of critical success index in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.842 delta-p value. Meanwhile the DDCA reached 0.561, HFAF reached 0.613 and RFHF reached 0.771 CSI values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.827 CSI value. Meanwhile the DDCA reached 0.574, HFAF reached 0.579 and RFHF reached 0.557 CSI values.

F. COMPUTATION OF ACCURACY (A)

The accuracy of a Cardiac Machine Learning Model (CMLM) is calculated by comparing the predicted results with the observed results. The CMLM accuracy depends on the quality of the model, the quality of the input data, the performance of the validation mechanism used in the model, and the performance of the prediction mechanism used in the model. To calculate the accuracy of the CMLM, first, the model's performance is assessed by splitting the data into training and test sets. The data to train the model must be sufficiently large and unbiased; otherwise, it may lead to over fitting or invalid predictions. The test set is then used to validate the model's performance. It is done by comparing the model's predicted outcomes with the observed outcomes in the test set. Two values are calculated from the test set to calculate the accuracy of the CMLM for early detection of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU). These values include sensitivity and specificity. The sensitivity measures the proportion of true positives correctly identified by the model. The specificity measures the proportion of true negatives correctly identified by the model. The model's accuracy is then calculated as the arithmetic mean of these two values.

Table 8, shows the various accuracy evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 12, demonstrates the Evaluation of accuracy in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.916 accuracy value. Meanwhile the DDCA reached 0.430, HFAF reached 0.489 and RFHF reached 0.613 accuracy values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.879 accuracy value. Meanwhile the DDCA reached 0.459, HFAF reached 0.552 and RFHF reached 0.669 accuracy values.

G. COMPUTATION OF PRECISION (P)

The precision of a CMLM for early detection of cardiac arrest in newborns in the CICU can be calculated by measuring the true positives (TP) out of the total number of positives (TP + False Positives (FP)). The true positives measure the percent of cases the model correctly identifies as cardiac arrest, while the false positives measure the percent of cases the model incorrectly identifies as cardiac arrest. The precision score

TABLE 8. Evaluation of accuracy.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.377	0.538	0.472	0.490	0.668	0.641	0.856	0.918
200	0.390	0.518	0.476	0.506	0.655	0.648	0.871	0.908
300	0.403	0.499	0.481	0.521	0.641	0.655	0.886	0.898
400	0.416	0.479	0.485	0.537	0.627	0.662	0.901	0.889
500	0.430	0.459	0.489	0.552	0.613	0.669	0.916	0.879
600	0.443	0.439	0.493	0.568	0.599	0.675	0.931	0.869
700	0.456	0.419	0.498	0.583	0.586	0.682	0.947	0.859
800	0.469	0.400	0.502	0.599	0.572	0.689	0.962	0.849
900	0.482	0.380	0.506	0.614	0.558	0.696	0.977	0.840
1000	0.496	0.360	0.511	0.630	0.544	0.703	0.992	0.830

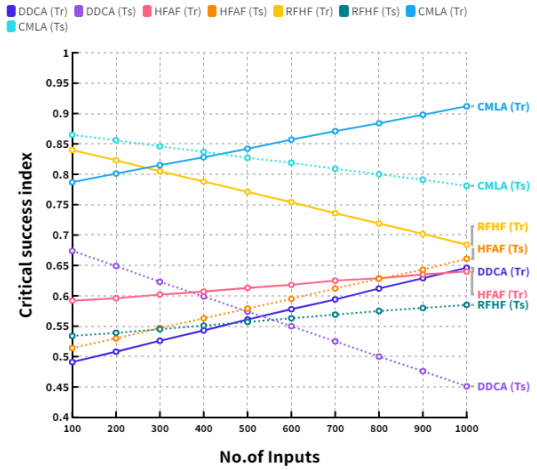

FIGURE 11. Evaluation of critical success index.

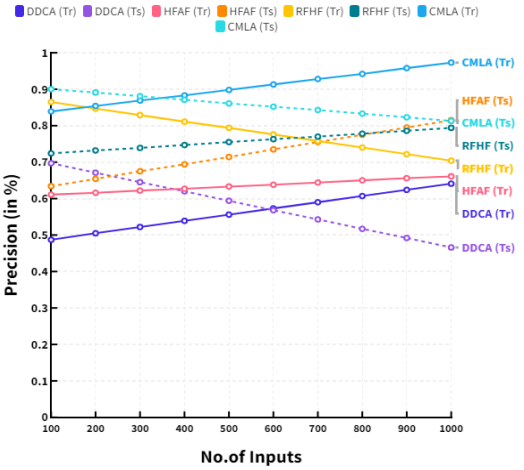

FIGURE 13. Evaluation of critical success index.

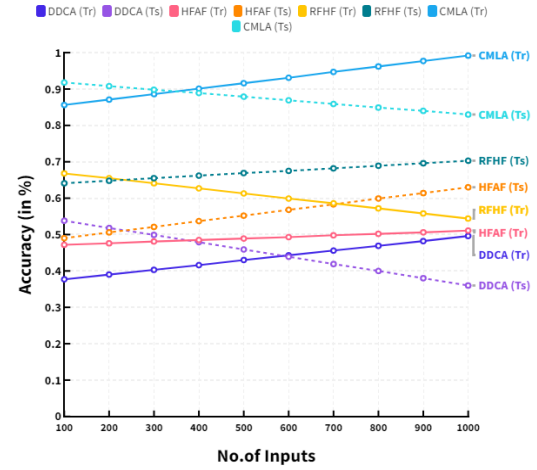

FIGURE 12. Evaluation of accuracy.

is then calculated by dividing the true positives by the total number of positives.

Table 9, shows the precision evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 13, demonstrates the Evaluation of precision in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.898 precision value. Meanwhile the DDCA reached 0.556, HFAF reached 0.633 and RFHF reached 0.794 precision values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.861 precision value. Meanwhile the DDCA reached 0.594, HFAF reached 0.714 and RFHF reached 0.755 precision values.

H. COMPUTATION OF RECALL (R)

The recall is a metric commonly used to evaluate classification models such as the CMLM. It measures the fraction of all positives (e.g., cardiac arrest babies) correctly classified as positive by the model. To calculate recall, we must first identify the true positives (TP) and false negatives (FN):

- TP = the number of babies the CMLM correctly identified as having a cardiac arrest,
- FN = the number of babies the CMLM incorrectly labeled as not having a cardiac arrest.

The recall score measures the model's ability to identify true positives. It thus indicates the CMLM's reliability for accurately detecting cardiac arrest in newborn babies in the CICU. Table 10, shows the various recall evaluations between

TABLE 9. Evaluation of precision.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.487	0.697	0.611	0.634	0.865	0.724	0.839	0.900
200	0.505	0.671	0.616	0.654	0.847	0.732	0.854	0.891
300	0.522	0.645	0.622	0.675	0.829	0.739	0.869	0.881
400	0.539	0.620	0.627	0.694	0.811	0.747	0.883	0.871
500	0.556	0.594	0.633	0.714	0.794	0.755	0.898	0.861
600	0.573	0.568	0.638	0.735	0.776	0.763	0.913	0.852
700	0.590	0.543	0.644	0.755	0.758	0.770	0.928	0.843
800	0.607	0.517	0.650	0.775	0.740	0.778	0.942	0.833
900	0.624	0.492	0.656	0.795	0.722	0.786	0.958	0.823
1000	0.641	0.466	0.661	0.815	0.704	0.794	0.973	0.813

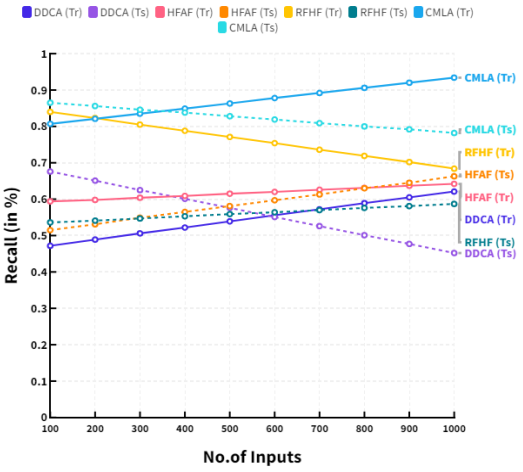

FIGURE 14. Evaluation of recall.

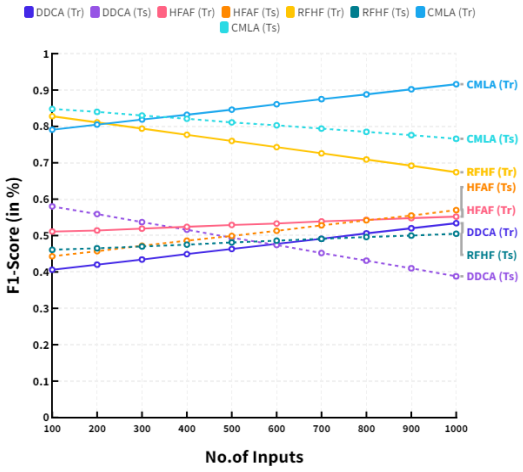

FIGURE 15. Evaluation of F1-score.

the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 14, demonstrates the Evaluation of recall in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.863 recall value. Meanwhile the DDCA reached 0.539, HFAF reached 0.615 and RFHF reached 0.771 recall values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.828 recall value. Meanwhile the DDCA reached 0.576, HFAF reached 0.581 and RFHF reached 0.559 recall values.

I. COMPUTATION OF F1-SCORE (F1)

The F1 score measures the accuracy of a model's prediction by combining precision and recall. Precision is the number of true positives divided by the total number of positives, while recall is the number of true positives divided by the total number of actual positives. The higher the F1 score, the better the model can correctly identify true positives. To compute the F1 score for the CMLM, we need to first look at the precision and recall of our model. Precision is the fraction of true positives (TP) out of all positives (TP+FP). The recall is the fraction of true positives out of all actual positives (TP+FN). In our case, TP is the number of cardiac arrests our model correctly identifies, FP is the number of false arrests, and FN is the number of cardiac arrests our model fails to identify. The F1 score can range from 0 to 1, with 0 indicating a terrible model and 1 indicating a perfect model. The higher the F1 score, the better the model identifies cardiac arrests. The final F1 score can be used to compare different models and determine the best identification of cardiac arrests in the CICU.

Table 11, shows the various F1-score evaluations between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

Fig. 15, demonstrates the Evaluation of F1-score in different level of inputs. In a training (Tr) comparison region, the proposed CMLA reached 0.846 F1-score value. Meanwhile the DDCA reached 0.463, HFAF reached 0.529 and RFHF reached 0.760 F1-score values respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.811 F1-score value. Meanwhile the DDCA reached 0.494, HFAF reached 0.499 and RFHF reached 0.481 F1-score values.

VI. RESULTS AND DISCUSSION

Statistical models can identify potential cardiac arrest cases in cardiac intensive care unit newborn babies. These models

TABLE 10. Evaluation of recall.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.472	0.676	0.594	0.515	0.840	0.536	0.807	0.865
200	0.489	0.651	0.598	0.531	0.823	0.541	0.821	0.856
300	0.506	0.625	0.604	0.549	0.805	0.547	0.835	0.846
400	0.522	0.601	0.609	0.565	0.788	0.553	0.849	0.838
500	0.539	0.576	0.615	0.581	0.771	0.559	0.863	0.828
600	0.556	0.551	0.620	0.597	0.754	0.564	0.878	0.819
700	0.572	0.526	0.626	0.613	0.736	0.570	0.892	0.809
800	0.589	0.501	0.631	0.630	0.719	0.576	0.906	0.800
900	0.605	0.477	0.637	0.645	0.702	0.581	0.920	0.792
1000	0.621	0.452	0.642	0.663	0.684	0.587	0.934	0.782

TABLE 11. Evaluation of F1-score.

No.of Inputs	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CML A (Ts)
100	0.406	0.580	0.511	0.443	0.828	0.461	0.791	0.848
200	0.420	0.559	0.514	0.457	0.811	0.465	0.805	0.840
300	0.434	0.537	0.519	0.472	0.794	0.470	0.819	0.830
400	0.449	0.516	0.524	0.486	0.777	0.475	0.832	0.821
500	0.463	0.494	0.529	0.499	0.760	0.481	0.846	0.811
600	0.477	0.474	0.533	0.513	0.743	0.486	0.861	0.803
700	0.491	0.452	0.539	0.528	0.726	0.491	0.875	0.794
800	0.506	0.431	0.543	0.542	0.709	0.496	0.888	0.785
900	0.520	0.410	0.548	0.555	0.692	0.500	0.902	0.776
1000	0.534	0.388	0.552	0.570	0.674	0.505	0.916	0.766

use data from monitoring devices, such as heart rate, blood pressure, and oxygen saturation, to detect abnormalities that may indicate a cardiac arrest. If a potential case is identified, the medical team can intervene quickly to provide the necessary care and treatment. Statistical models can detect changes in vital signs over time and identify any risk factors that may increase the likelihood of cardiac arrest in a newborn. In addition, these models can be used to analyze ICU data to identify trends or patterns that may indicate a higher risk of cardiac arrest. Using statistical models, medical teams can identify potential cases of cardiac arrest early and intervene quickly to provide the necessary care and treatment.

$$C = \left\{ \frac{\sum_{i=1}^{n} A_i(x)}{\sum_{i=1}^{n} Z_i(x)} \right\}; \tag{20}$$

where, C represents the convergence of performance, 'i' is the initial input level, 'n' is the final input level. 'A' represents the average value of the performance parameter and 'Z' represents the total number of training or testing cycles. Table 12, shows the various convergence of performance between the proposed and existing models. In that Tr represents the training data and Ts represents the testing data.

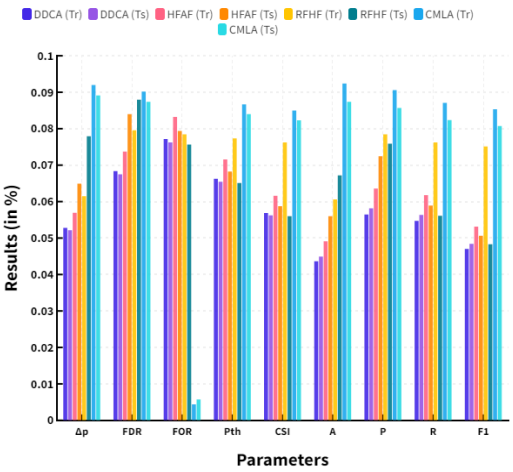

FIGURE 16. Convergence of performance.

Fig. 16, demonstrates the convergence of performance between existing and proposed models. In a training (Tr) comparison region, the proposed CMLA reached 0.09195 delta-P value, 0.09015 false discovery rate, 0.00438 false omission rate, 0.08665 prevalence threshold, 0.08495 critical success index values, 0.09239 accuracy, 0.09057 precision,

TABLE 12. Evaluation of convergence of performance.

Parameters	DDCA (Tr)	DDCA (Ts)	HFAF (Tr)	HFAF (Ts)	RFHF (Tr)	RFHF (Ts)	CMLA (Tr)	CMLA (Ts)
Δp	0.0528	0.05215	0.05695	0.0649	0.0615	0.0779	0.09195	0.0891
FDR	0.06833	0.06749	0.0737	0.08399	0.07958	0.08795	0.09015	0.08735
FOR	0.07716	0.07623	0.08323	0.07936	0.07844	0.07565	0.00438	0.00574
P_{th}	0.06625	0.06546	0.07158	0.06826	0.07732	0.06508	0.08665	0.08396
CSI	0.05688	0.05621	0.06157	0.05872	0.07622	0.05598	0.08495	0.08231
A	0.04362	0.04491	0.04913	0.056	0.06063	0.0672	0.09239	0.08739
P	0.05644	0.05813	0.06358	0.07246	0.07846	0.07588	0.09057	0.08568
R	0.05471	0.05636	0.06176	0.05889	0.07622	0.05614	0.08705	0.08235
F1	0.047	0.04841	0.05312	0.05065	0.07514	0.0483	0.08535	0.08074

0.08705 recall and 0.08535 f1-score. Meanwhile the DDCA reached 0.0528 delta-P value, 0.06833 false discovery rate, 0.07716 false omission rate, 0.06625 prevalence threshold, 0.05688 critical success index values, 0.04362 accuracy, 0.05644 precision, 0.05471 recall, 0.047 F1-Score, HFAF reached 0.05695 delta-P value, 0.0737 false discovery rate, 0.08323 false omission rate, 0.07158 prevalence threshold, 0.06157 critical success index values, 0.04913 accuracy, 0.06358 precision, 0.06176 recall and 0.05312 F1-Score and RFHF reached 0.0615 delta-P value, 0.07958 false discovery rate, 0.07844 false omission rate, 0.07732 prevalence threshold, 0.07622 critical success index values, 0.06063 accuracy, 0.07846 precision, 0.07622 recall and 0.07514 F1-Score respectively. In a testing (Ts) comparison region, the proposed CMLA reached 0.0891delta-P value, 0.08735 false discovery rate, 0.00574 false omission rate, 0.08396 prevalence threshold, 0.08231 critical success index values, 0.08739 accuracy, 0.08568 precision, 0.08235 recall and 0.08074 F1-score. Meanwhile the DDCA reached 0.05215 delta-P value, 0.06749 false discovery rate, 0.07623 false omission rate, 0.06546 prevalence threshold, 0.05621 critical success index values 0.04491 accuracy, 0.05813 precision, 0.05636 recall and 0.04841 F1-score, HFAF reached 0.0649 delta-P value, 0.08399 false discovery rate, 0.07936 false omission rate, 0.06826 prevalence threshold, 0.05872 critical success index values, 0.056 accuracy, 0.07246 precision, 0.05889 recall and 0.05065 F1-score and RFHF reached 0.0779 delta-P value, 0.08795 false discovery rate, 0.07565 false omission rate, 0.06508 prevalence threshold, 0.05598 critical success index values, 0.0672 accuracy, 0.07588 precision, 0.05614 recall and 0.0483 F1-score respectively. Hence mean value of the performance parameters has shown in the following eq.21.

$$M = C_{tr} - C_{Ts}; \tag{21}$$

where, M represents the mean value, C_{tr} represents the convergence of performance training data and C_{ts} represents the convergence performance of the testing data. Table 13, expresses the mean value of the performance parameters

TABLE 13. Evaluation of mean of performance.

Parameters	DDCA	HFAF	RFHF	CMLA
Δp	0.00065	-0.00795	-0.0164	0.00285
FDR	0.00084	-0.01029	-0.00837	0.0028
FOR	0.00093	0.00387	0.00279	-0.00136
P_{th}	0.00079	0.00332	0.01224	0.00269
CSI	0.00067	0.00285	0.02024	0.00264
A	-0.00129	-0.00687	-0.00657	0.005
P	-0.00169	-0.00888	0.00258	0.00489
R	-0.00165	0.00287	0.02008	0.0047
F1	-0.00141	0.00247	0.02684	0.00461

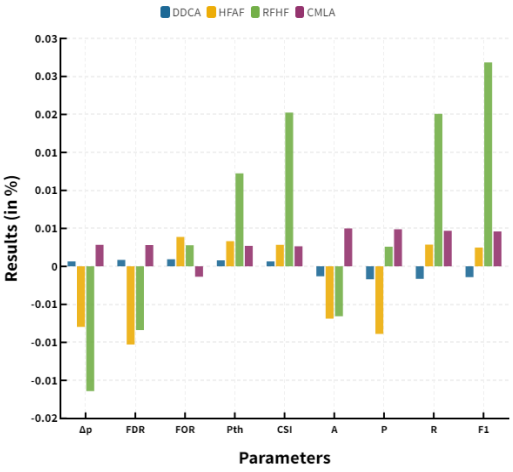

FIGURE 17. Mean values of the performance parameters.

Fig. 17, shows the mean values of the performance parameters. The proposed CMLA reached 0.00285 mean delta-P value (m-Δp), 0.0028 mean false discovery rate (m-FDR), −0.00136 mean false omission rate (m-FOR), 0.00269 mean prevalence threshold (m-Pth), 0.00264 mean critical success index (m-CSI) values, 0.005 accuracy, 0.00489 precision, 0.0047 recall and 0.00461 F1-score. Meanwhile the DDCA reached 0.00065 mean delta-P value (m-Δp), 0.00084 mean false discovery rate (m-FDR),

0.00093 mean false omission rate (m-FOR), 0.00079 mean prevalence threshold (m-Pth), 0.00067 mean critical success index (m-CSI) values, −0.00657 accuracy, 0.00258 precision, 0.02008 recall and 0.02684 F1-score, HFAF reached −0.00795 mean delta-P value (m-Δp), −0.01029 mean false discovery rate (m-FDR), 0.00387 mean false omission rate (m-FOR), 0.00332 mean prevalence threshold (m-Pth) and 0.00285 mean critical success index (m-CSI) values, −0.00687 accuracy, −0.00888 precision, 0.00287 recall and 0.00247 F1-score and RFHF reached −0.0164 mean delta-P value (m-Δp), −0.00837 mean false discovery rate (m-FDR), 0.00279 mean false omission rate (m-FOR), 0.01224 mean prevalence threshold (m-Pth) 0.02024 mean critical success index (m-CSI) values, −0.00129 accuracy, −0.00169 precision, −0.00165 recall and −0.00141 F1-score respectively. While compared with the existing models, the proposed CMLA model achieved better convergence and mean values. The Cardiac Machine Learning Model for Early Prediction of Sepsis in the ICU is an innovative predictive model that can accurately identify sepsis in Intensive Care Units (ICUs) before it becomes life-threatening. This model uses a combination of supervised and unsupervised machine learning algorithms to identify sepsis in ICU patients at an early stage. The model uses clinical data, such as vital signs and laboratory parameters, along with patient notes to detect sepsis accurately. This data is then used to create a predictive model that can accurately identify sepsis at an early stage. The model can also identify subtle changes in patients' conditions that could indicate sepsis, allowing for early intervention and treatment. The Cardiac Machine Learning Model for Early Prediction of Sepsis in the ICU using Machine Learning is an innovative and accurate predictive model that can save lives by detecting sepsis before it becomes life-threatening. It is a highly effective tool for doctors and nurses in ICUs looking to quickly and accurately detect sepsis in their patients.

VII. CONCLUSION

The proposed machine learning-based statistical model is essential for the early detection of cardiac arrest in newborn babies in the Cardiac Intensive Care Unit (CICU) because they enable the efficient and accurate identification of infants at high risk of cardiac arrest. Machine learning models can accurately identify subtle changes in vital signs, such as heart and respiration rates, that may indicate an impending cardiac arrest. In a training (Tr) comparison region, the proposed CMLA reached 0.912 delta-p value, 0.894 FDR value, 0.076 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. The proposed cardiac machine learning model to identify at-risk infants, healthcare providers can provide early intervention that may help to avert a tragic outcome. Early detection of cardiac arrest can also reduce the amount of time an infant spends in the CICU, helping to reduce costs and improve outcomes. Future enhancements of the proposed model will focus on using real-time data to identify critical indicators of cardiac arrest. It can involve collecting various data types such as heart rate, breathing rate, temperature, and other physiological measures. The cardiac machine learning algorithms can then be used to analyze this data to develop models that can accurately predict the likelihood of cardiac arrest. The proposed model can then be used to alert medical staff in order to allow for earlier and more effective interventions. Future enhancements may also include using artificial intelligence to detect patterns in the data and make more accurate predictions. It could incorporate data from other sources, such as previous records and medical histories. Finally, these models could be used to develop personalized interventions for individual patients, allowing for more effective treatments. Enhancing the proposed machine learning algorithm could also pave the way for predicting potential complications in fetuses or newborns. A healthcare team can determine risk levels for specific cardiac abnormalities before a baby is even born, which helps provide better interventions during the prenatal period. In addition, the proposed machine learning algorithm could be used to improve diagnostics and treatments. By studying historical patient data, diagnostics can be improved, and doctors can be presented with more accurate and up-to-date information when diagnosing a patient. It can lead to earlier interventions, better patient outcomes, and more cost-effective treatments.

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