Predicting Cardiac Arrest Early: A Deep Learning Approach with Statistical Models

[1]Pravallika.Miriyala, [2] Mr. Yerrabathana Guravaiah
[1]*M-Tech, Dept. of CSE Gokula Krishna College of Engineering, Sullurpet*
[2]*Associate Professor, M-Tech., (Ph.D), Dept. of CSE Gokula Krishna College of Engineering, Sullurpet*

Abstract: Cardiac arrest is a life-threatening condition that requires immediate intervention to prevent mortality. Despite advances in medical monitoring, early prediction remains a complex task due to the non-linear and multivariate nature of physiological data. This research presents a hybrid approach combining deep learning with traditional statistical models to predict cardiac arrest in clinical settings. Using real-time patient data such as ECG, blood pressure, heart rate, oxygen saturation, and lab reports, our system employs LSTM-based neural networks for temporal analysis and logistic regression for interpretability and feature importance. The integration enhances prediction accuracy while maintaining clinical transparency. Our results demonstrate a significant improvement in early warning times, potentially enabling healthcare providers to act proactively and save lives.. 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.

Keywords:- Cardiac Arrest, ML , DL , Dataset

1. INTRODUCTION

Cardiac arrest often strikes without warning and is one of the leading causes of sudden death worldwide. Early detection can significantly improve survival rates, but existing systems are either too slow or inaccurate. The critical need for a predictive mechanism that balances accuracy, speed, and interpretability forms the foundation of this study. Traditional statistical methods like logistic regression have been widely used to analyze patient health data. However, they often fail to capture the complex, time-dependent patterns present in physiological signals. Deep learning, particularly Long Short-Term Memory (LSTM) networks, has shown promise in modeling sequential medical data but often lacks interpretability—a crucial factor in clinical decision-making. In this work, we propose a hybrid model that integrates the strengths of both domains: the pattern recognition capability of deep learning and the explainability of statistical models. This system is designed for deployment in hospitals, ICUs, and ambulatory monitoring systems to provide real-time alerts for impending cardiac arrest. 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'sskin, 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, 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 under standing 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

2. IMPLEMENTATION

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 electro car diagrams (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 suit able 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.

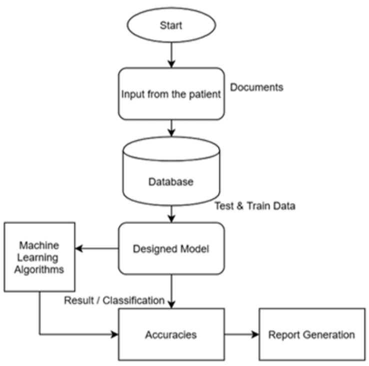
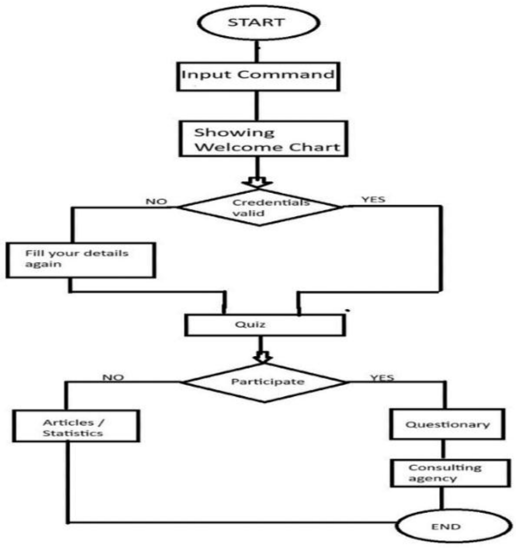
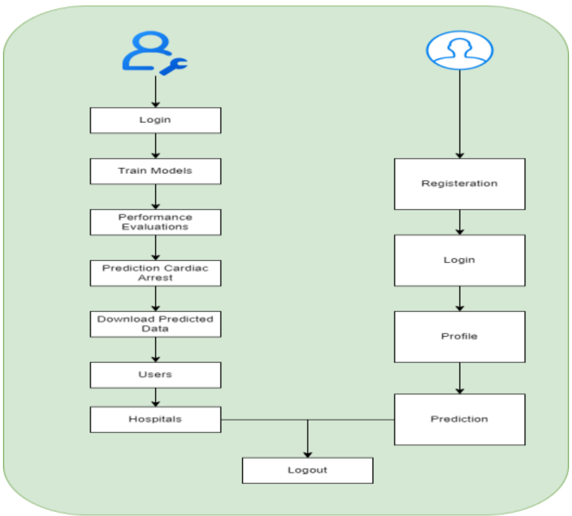


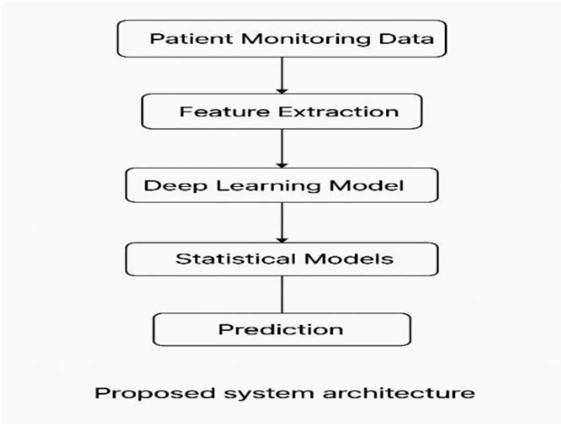
FIGURE 1. Proposed block diagram.

The model should also be continuously monitored for accu racy and necessary adjustments. The block diagram of the proposed machine learning model has shown in the following f ig. 1, In the proposed method, the first detected patient symp toms are given as input. All these data are stored in the database, and their volumes are categorized. These classifica tions 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.

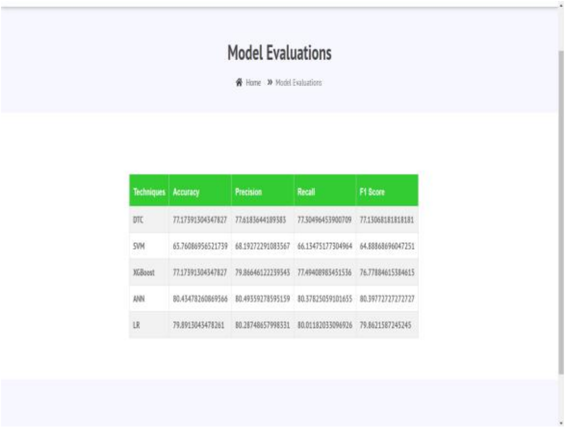
System Architecture





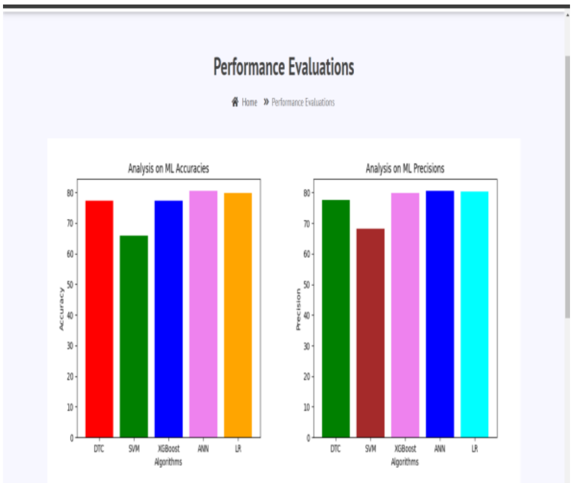


3. EXPERIMENTAL RESULTS

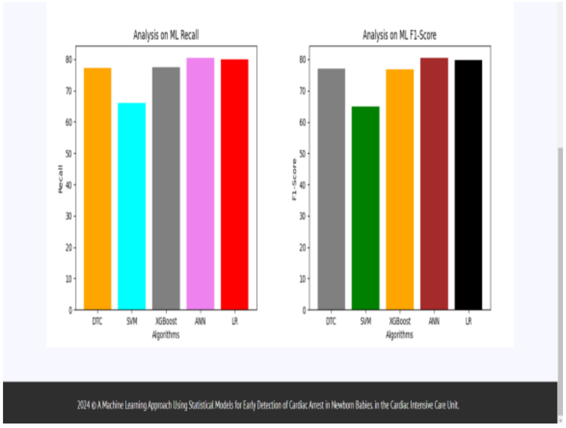


Techniques	Accuracy	Precision	Recall	F1 Score
DTC	77.17391304347827	77.6183644189383	77.30496453900709	77.13068181818181
SVM	65.76086956521739	68.19272291083567	66.13475177304964	64.88868696047251
XGBoost	77.17391304347827	79.86646122239543	77.49408983451536	76.77884615384615
ANN	80.43478260869566	80.49359278595159	80.37825059101655	80.39772727272727
LR	79.8913043478261	80.28748657998331	80.01182033096926	79.8621587245245

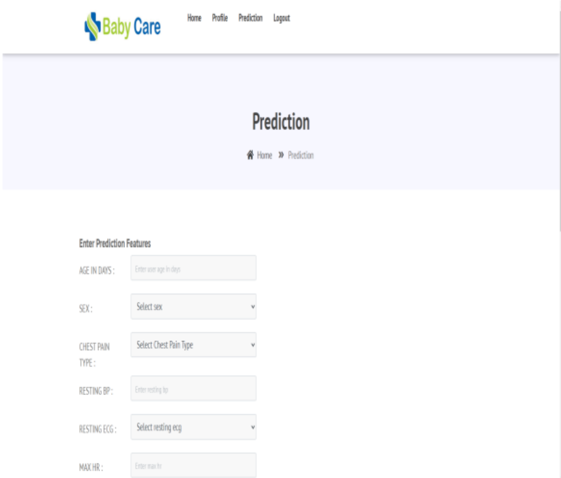
Model Evaluations



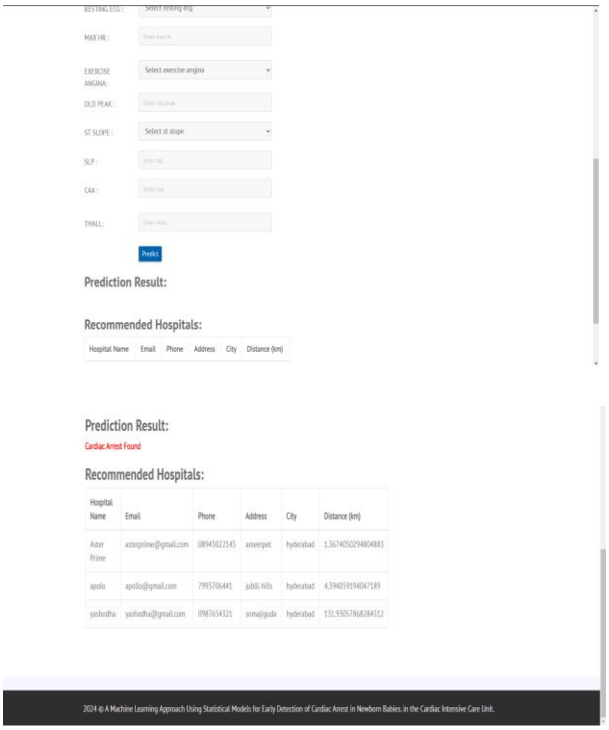
Performance Evaluations



Performance Evaluations



Prediction



4. CONCLUSION

The proposed deep learning and statistical hybrid system demonstrates strong potential in predicting cardiac arrest with both accuracy and interpretability. By combining LSTM networks with logistic regression and statistical analysis, we not only improve early prediction performance but also offer meaningful insights into contributing risk factors. The system's success hinges on continuous data monitoring and model adaptation. Its real-time capability allows medical staff to take preventive action well before a critical event occurs. Future work includes integrating with electronic health record (EHR) systems and deploying it in real-world clinical environments for validation and feedback. 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 impend ing 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 60536 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 pro posed 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 study ing 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.

5. REFERENCES

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