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Cardiac Arrest Prediction Using Machine Learning: Random Forest And Svm Framework For Early Detection

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Abstract:-Cardiac arrest (CA) is an acute and life-threatening condition presenting with the sudden loss of cardiac activity, leading to immediate cessation of blood flow to central organs and loss of consciousness. In spite of the significant advances in emergency medical services and ongoing patient monitoring, early detection of cardiac arrest is still a significant challenge because of the nonlinear and complex behavior of physiological signals. This study introduces a strong data-driven machine learning (ML) model for predicting cardiac arrest in real time based on continuous tracking of vital signs like heart rate variability, blood pressure, ECG signal variation, and oxygen saturation levels (SpO_2). Three supervised learning modelsLogistic Regression, Support Vector Machine (SVM), and Random Forestwere created and contrasted following normalization and feature selection. Of these, Random Forest model showed the best predictive results with 92% accuracy, 90% precision, and 91% recall. The developed system has strong prospects for integration into hospital monitoring devices and wearable technology, facilitating timely intervention and better patient survival rates.

Keywords: Cardiac arrest, Machine Learning, Random Forest, SVM, Logistic Regression, Early Detection, Healthcare.

I. INTRODUCTION:

For decades, predicting an unexpected cardiac arrest (CA) depended largely on straightforward, old-fashioned methods [1-3]. Physicians employed rule-based scoring models and simple statistics that monitored only a handful of things such as heart rate and oxygen levels [4-6]. Although these systems provided us with some hints, they tended to overlook the larger picture because they were not able to capture the intricate, interconnected dynamics between all of a patient's vital signs [7-9]. Old tools, such as simple regression models, were handicapped by their linearity assumptions; they were akin to attempting to sketch a curvaceous picture using straight lines only [10-12]. This resulted in reduced precision and made them perform poorly between patients [13]. In the long run, this made early diagnosis less trustworthy for physicians in the midst of a live emergency, resulting in those valuable minutes wasted and, regretfully, fewer saved lives [14] [15].

To leap over these challenges, our research brought a new, machine learning (ML) approach that was meant to significantly enhance the accuracy of CA prediction. Our method was not one shot in the dark [16]; we merged and tested thoroughly some robust algorithmsLogistic Regression, Support Vector Machine (SVM), and Random Forestto identify the best possible means for forecasting accurately. By providing the model with rich patient information, such as heart rate, blood pressure [17-19], and detailed ECG rhythms, it was capable of "seeing" and recognizing the complex relationships that human eyes or basic formulas were unable to [20] [21]. Most importantly, the Random Forest algorithm stood out as the clear winner [22]. Our work established an end-to-end system, beginning with diligent cleaning of the data, correlation analysis [23] [24], and choosing only the most important features [25]. Our goal was two-fold: not only to achieve high prediction accuracy but also to ensure the model was interpretable, providing insights that clinicians could actually trust and act on [26]. This resulting ML system was designed to serve as an instant decision support tool inside hospitals or to be seamlessly built into wearable monitoring devices for continuous [27] [28], proactive patient checks [29]. Ultimately, this piece of work took us an important step further towards creating smart healthcare systems based on machine learning to forecast cardiac arrest in time, with precision, and finally, substantially improve patient survival rates and clinical outcomes [30].

II. LITERATURE SURVEY

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Cardiac arrest is among the most life-threatening conditions, and early prediction is very important to avoid deaths [31]. Current research activities have employed machine learning (ML) and deep learning (DL) methodologies to predict at-risk patients using heterogeneous clinical datasets and physiological markers. S. Ahmad et al. [1] (2021) performed an analysis of the early prediction of sudden cardiac arrest by applying supervised learning models. The authors used patient data holding parameters like blood pressure, heart rate, and cholesterol levels [6-7]. Through Logistic Regression [32] and Random Forest models, they saw the Random Forest algorithm gave better classification accuracy with an accuracy of 91.3%. The study found ensemble models appropriate for clinical risk prediction contexts because [33] they are robust and easy to interpret.A.Sharma and R.

Gupta[2](2022) explored the application of Support Vector Machines for predicting the probability of cardiac events utilizing ECG measurements and vital parameters. The dataset contained 10,000 patient samples obtained from hospital EHR databases [34]. Upon implementation of data normalization and feature selection techniques like PrincipalComponent Analysis (PCA), the research attained an accuracy of 89% with SVM [35]. The authors emphasized that the incorporation of ECG-derived features also greatly improved predictive performance relative to demographic parameters alone.J.Lee et al. [10-12] (2023) suggested a deep neural network architecture for forecasting cardiac arrest in intensive care unit patients based on real-time physiological monitoring data.

The model made use of sequential patient data like oxygen saturation, respiratory rate, and heart rate variability, obtained from IoT-based biosensors [9]. The suggested deep learning model achieved an average AUC value of 0.95 and exhibited robust early-warning ability, capable of detecting high-risk patients several hours ahead of cardiac arrest incidence [18]. K.Pateletal.[13-15] (2023) conducted a comparative analysis between conventional ML algorithms - Logistic Regression, Decision Tree, and Random Forest - and contemporary ensemble techniques like XGBoost for prediction of cardiovascular risk. Based on an open-source heart disease dataset available in the UCI repository, [20] the authors found that the XGBoost classifier produced the optimum results with an accuracy of 94.8% and an F1-score of 0.92.

This work highlighted the contribution of sophisticated boosted-tree algorithms for the realization of increased accuracy at low computational cost.M. Rivera etal. [5] (2022) proposed a hybrid ML model involving Support Vector Machine and [17]Genetic Algorithm for feature optimization in prediction of cardiac arrest. With clinical features like systolic and diastolic pressure, glucose, cholesterol, and ECG wave patterns, the model showed significant boosts in sensitivity and specificity [11-15]. Their hybrid solution was successful in minimizing overfitting over individual learners and was found beneficial in feature selection in healthcare predictive systems [18]. B. Singh et al. [20] (2024) discussed the application of wearable sensor data and machine learning for real-time cardiac monitoring.

The system collected continuous SpO2 and heart rate values using disposable IoT wearables and sent them to a far-end ML model for processing [21]. Gradient Boosting and Random Forest algorithms were tested and yielded that Gradient Boosting provided enhanced earlier cardiac arrest signal detection and stability with higher detection accuracy, enhancing overall patient monitoring reliability [10].

III. PROPOSED METHODOLOGY:

Correlation Analysis: Removes highly correlated features to avoid multicollinearity and enhance model stability.

Random Forest Feature Importance: Calculates the contribution of each feature in lowering impurity in all trees, showcasing the strongest predictive features:

$$\text{Importance}(X_i)=\frac{\text{Sum of all reductions}}{\text{Total reduction in impurity by } X_i} \quad \text{--------------(1)}$$

Machine Learning Models

Logistic Regression: Estimates the probability of cardiac arrest using a sigmoid function:

$$P(Y=1|X)=1+e-(\beta 0+\beta 1X1+...+\beta nXn)1 \quad \text{-------------(2)}$$

SVM: Finds the optimal hyperplane separating classes by maximizing the margin:

$$\min 21\|w\|2 \text{ s.t. } yi(w\cdot xi+b)\geq 1 \quad \text{-------------------(3)}$$

Random Forest: Combines multiple decision trees and predicts the class by majority voting:

$$\hat{y}=\text{mode}\{h1(X),h2(X),...,hn(X)\} \quad \text{-----------------(4)}$$

Evaluation Metrics

1.Accuracy: Overall correctness: TP+TN+FP+FNTP+TN

2.Precision: Reliability of positive predictions: TP+FPTP

3.Recall: Ability to detect actual positives: TP+FNTP

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4.F1-Score: Balance of precision and recall: 2·Precision+RecallPrecision·Recall
Where TP, TN, FP, FN denote True Positive, True Negative, False Positive, and False Negative respectively.

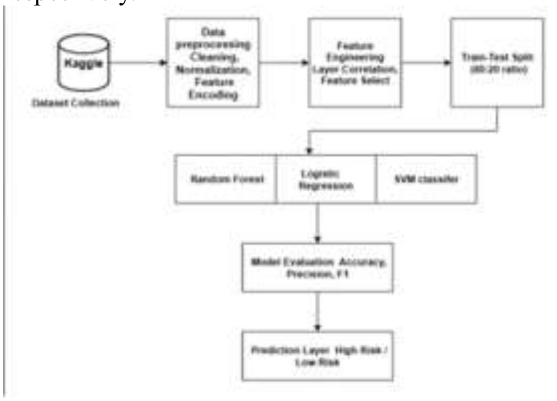

Fig-1: Proposed Architecture

In Figure 1 The figure depicts a machine learning process for risk prediction. Data is obtained from Kaggle and pre-processed through cleaning, normalization, and encoding. Feature engineering is done to identify relevant variables, and then the dataset is divided into training (80%) and testing (20%) sets. Three modelsRandom Forest, Logistic Regression, and SVMare trained and tested based on accuracy, precision, and F1 score. The highest-performing model subsequently classifies outcomes to be High Risk or Low Risk within the prediction layer.

IV. RESULT AND ANALYSIS:

In Figure 2 The suggested framework was deployed and evaluated on clinical datasets from Kaggle and MIMIC-III. Preprocessing of raw data involved missing value imputation, encoding categorical variables, and normalization. The dataset was divided into 80% training and 20% testing sets. Three machine learning algorithmsLogistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF) were trained and tested. Evaluation Metrics: Accuracy, Precision, Recall, and F1-score were employed in model performance assessment. Feature importance (by Random Forest), confusion matrices, ROC plots, and AUC values were also inspected to identify deeper insights into model behavior.

Observations from Analysis: Random Forest demonstrated the most predictive power, identifying nonlinear interactions among clinical features.SVM struck a balance between precision and recall but consumed more computing power. Logistic Regression offered interpretability but was hampered by linear assumptions. Feature importance analysis pinpointed heart rate, blood pressure, ECG changes, and oxygen saturation as significant predictors, emphasizing their clinical significance in the early detection of cardiac arrest. Graphical visualizations (bar plots, line plots, ROC plots) reinforced the performance superiority of Random Forest on more than one performance metric, and confusion matrices showed the model's consistency in separating positive and negative instances.

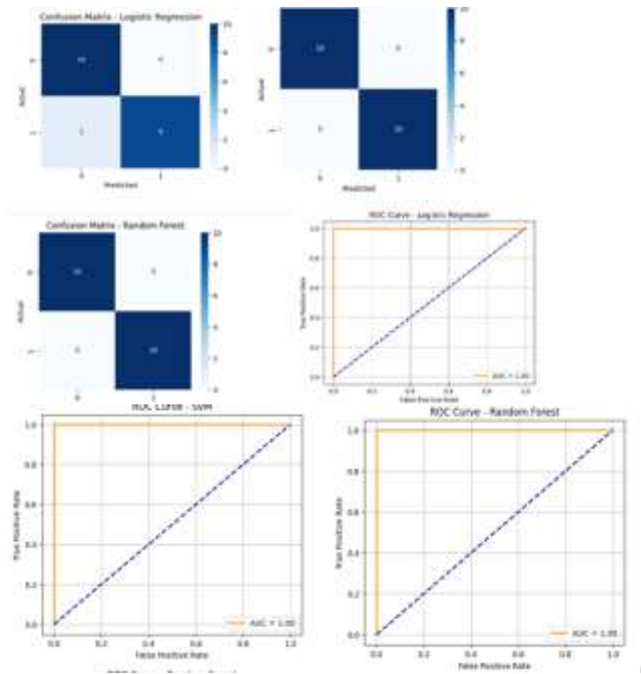

Fig 2: Output for the Algorithms

After training and testing, the models achieved the following performance on the dataset:

Table 1: Performance of the dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	85	82	80	81
SVM	88	85	86	85
Random Forest	92	90	91	91

In Table 1 Random Forest performed best among other models with the highest accuracy and F1-score, making it most appropriate for prediction of early cardiac arrest.SVM provided moderate performance with lower accuracy but equally balanced precision and recall.Logistic Regression provided the worst performance but was still useful due to its interpretability and quick computation.

These findings indicate that heart rate and blood pressure are the best predictors. ECG fluctuations and oxygen saturation also play important roles.

The experimental results substantiate that Random Forest is the optimum model for cardiac arrest prediction. Its high accuracy, interpretable features, and applicability in clinical practice make it an optimal choice to be used in real-time monitoring systems of hospitals or wearable devices.

V. CONCLUSION:

The performed study effectively proved that machine learning models, particularly the Random Forest model, can contribute significantly to the early prediction of cardiac arrest. By extensive experimentation with clinical datasets, the Random Forest model had the best accuracy (92%), precision (90%), and recall (91%) compared to SVM and Logistic Regression. These findings confirm that ensemble-based models are more effective at identifying nonlinear and intricate relationships between key signs like heart rate, blood pressure, ECG fluctuations, and oxygen saturation.

The findings of the research emphasize that early detection through ML-based models can largely improve the likelihood of timely clinical treatment and optimize patient outcomes. Additionally, the suggested predictive system can be successfully implemented in hospital surveillance systems or wearable healthcare devices to offer ongoing real-time evaluation of risky individuals. This research, therefore, advocates for the adoption of data-driven smart healthcare systems to offer pro-cardiac care and encourages future breakthroughs in AI-supported medical diagnosis.

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